TAIWAN TECH
NATIONAL TAIWAN UNIVERSITY OF SCIENCE AND TECHNOLOGY

NTPU
國立臺北大學
National Taipei University

# 智慧金融量化分析
# Artificial Intelligence in Finance and Quantitative Analysis

Host: Prof. Yi-Ling Chen

Computer Science and Information Engineering, National Taiwan University of Science and Technology

Time: 14:00-15:00, Dec. 6, 2021 (Monday)

Place: AU-101, CSIE, NTUST

Address: No.43, Keelung Rd., Sec.4, Da'an Dist., Taipei, Taiwan

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aws certified Solutions Architect Associate


## 戴敏育 副教授
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## 國立臺北大學 資訊管理研究所
## Institute of Information Management, National Taipei University

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2021-12-06

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## 中央研究院 資訊科學研究所 訪問學人
## 國立臺灣大學 資訊管理 博士

**Publications Co-Chairs, IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM 2013- )**

**Program Co-Chair, IEEE International Workshop on Empirical Methods for Recognizing Inference in TExt (IEEE EM-RITE 2012- )**

**Publications Chair, The IEEE International Conference on Information Reuse and Integration for Data Science (IEEE IRI)**

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國立臺灣大學

# Outline

- **AI in FinTech: Financial Services Innovation and Application**
- **Artificial Intelligence for Knowledge Graphs of Cryptocurrency Anti-money Laundering in Fintech**

# AI in Finance and Quantitative Analysis

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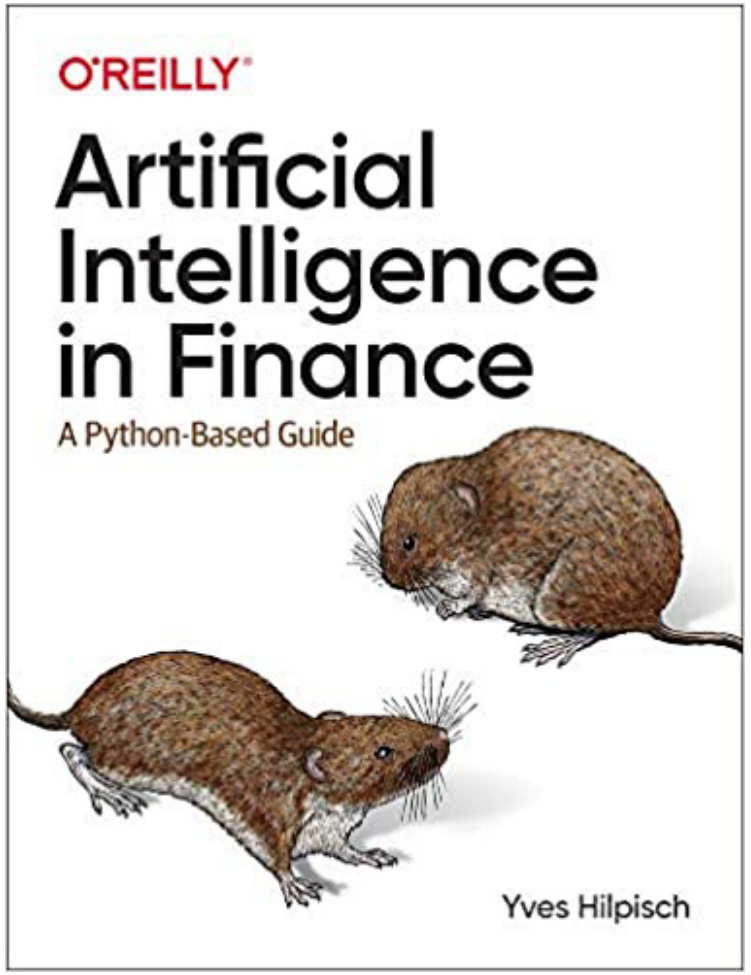
1. AI in FinTech: Financial Services Innovation and Application
2. Investing Psychology and Behavioral Finance
3. Event Studies in Finance
4. Finance Theory
5. Data-Driven Finance
6. Financial Econometrics
7. AI-First Finance
8. Deep Learning in Finance
9. Reinforcement Learning in Finance
10. Algorithmic Trading, Risk Management
11. Trading Bot and Event-Based Backtesting
12. Case Study on AI in Finance and Quantitative Analysis

# Yves Hilpisch (2020),

# Artificial Intelligence in Finance:

# A Python-Based Guide,

## O'Reilly



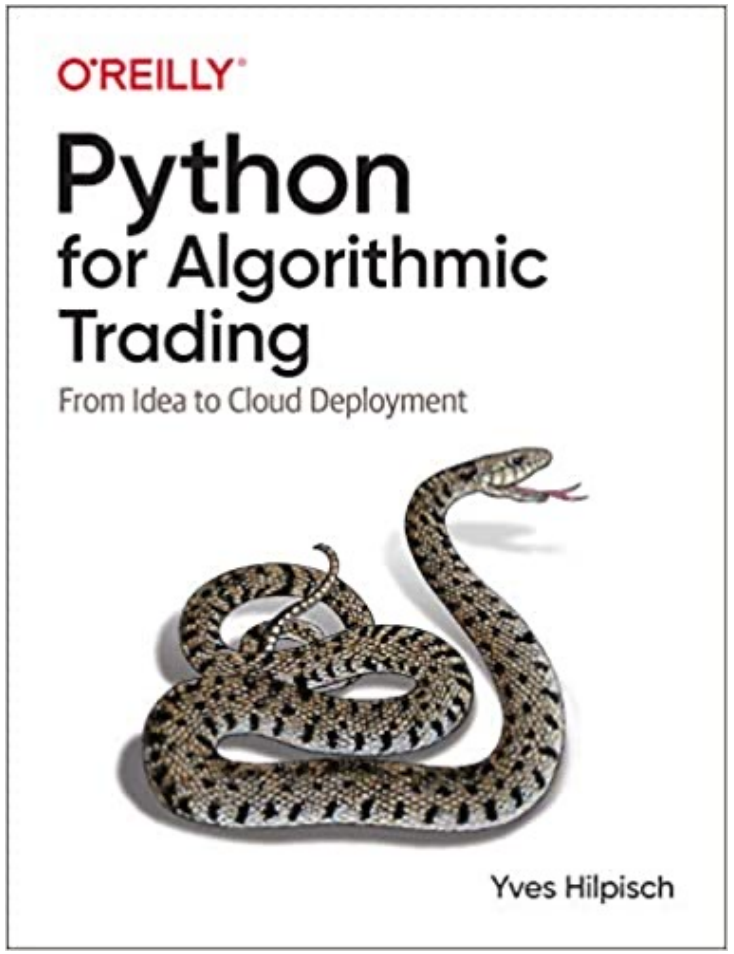

Source: https://www.amazon.com/Artificial-Intelligence-Finance-Python-Based-Guide/dp/1492055433

# Yves Hilpisch (2020),

# Python for Algorithmic Trading:

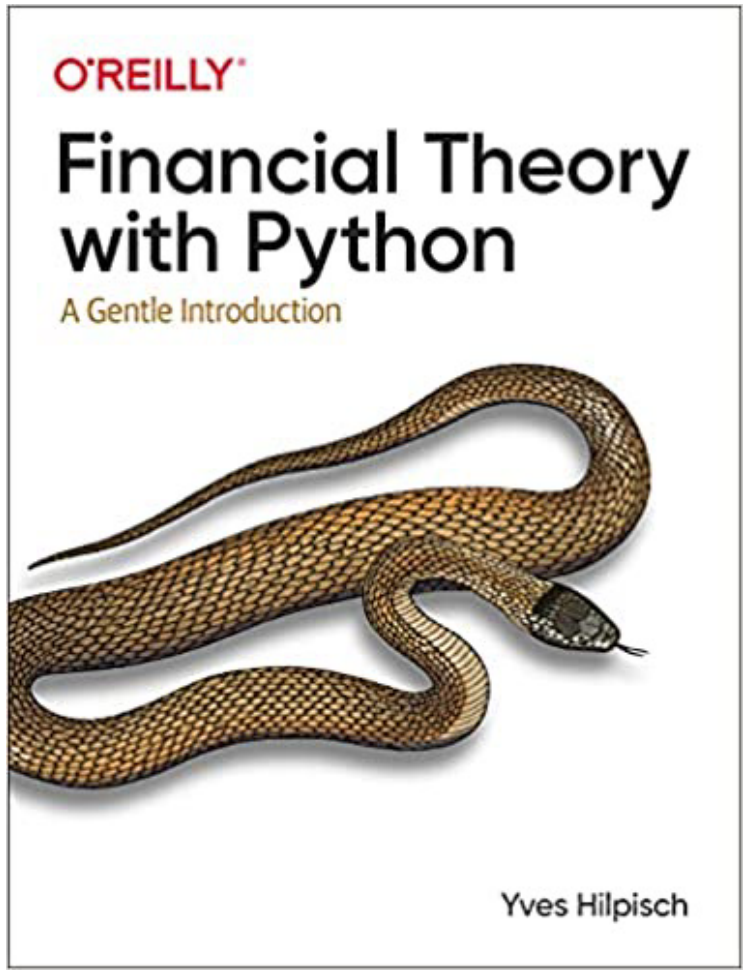
## From Idea to Cloud Deployment,

## O'Reilly




Source: https://www.amazon.com/Python-Algorithmic-Trading-Cloud-Deployment/dp/149205335X

# Yves Hilpisch (2021),
# Financial Theory with Python:
# A Gentle Introduction,
## O'Reilly

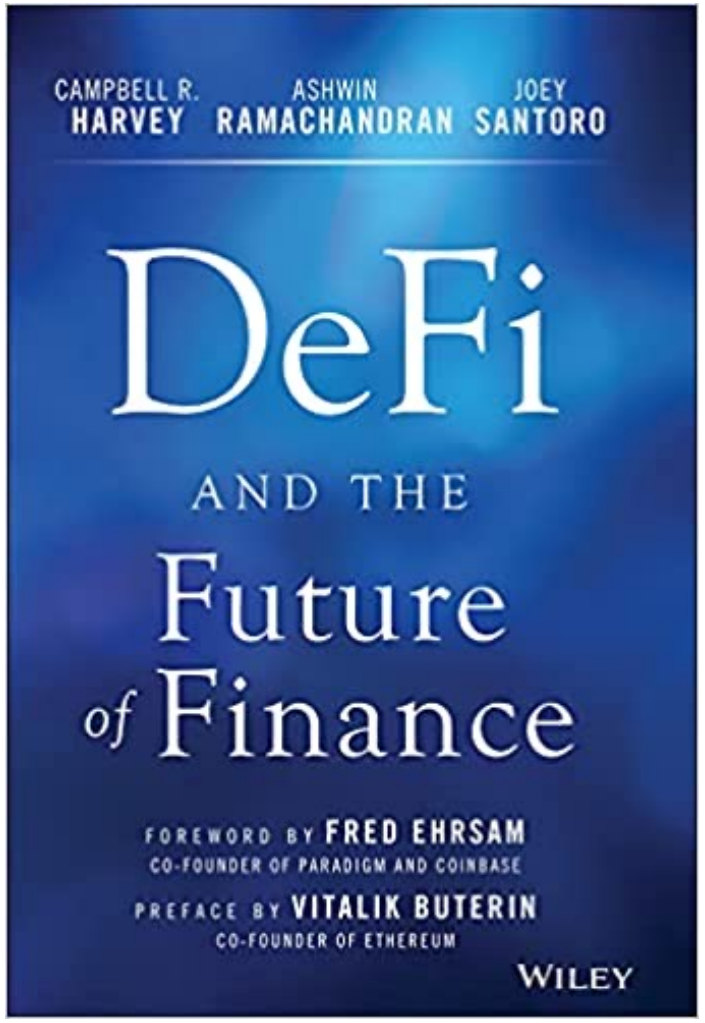



Source: https://www.amazon.com/Financial-Theory-Python-Gentle-Introduction/dp/1098104358

## Campbell R. Harvey, Ashwin Ramachandran, Joey Santoro, Fred Ehrsam (2021),

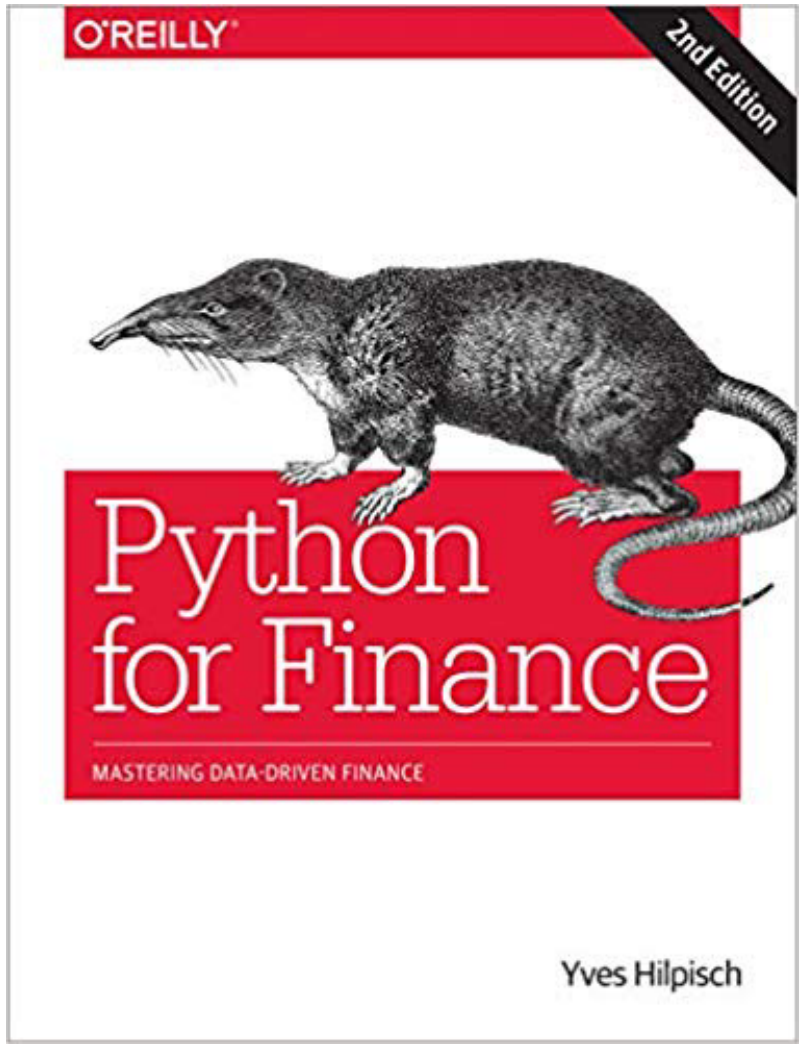
# DeFi and the Future of Finance,

## Wiley




Source: https://www.amazon.com/DeFi-Future-Finance-Campbell-Harvey-ebook/dp/B09DJV2QLC

# Yves Hilpisch (2018),
# Python for Finance: Mastering Data-Driven Finance,
## O'Reilly

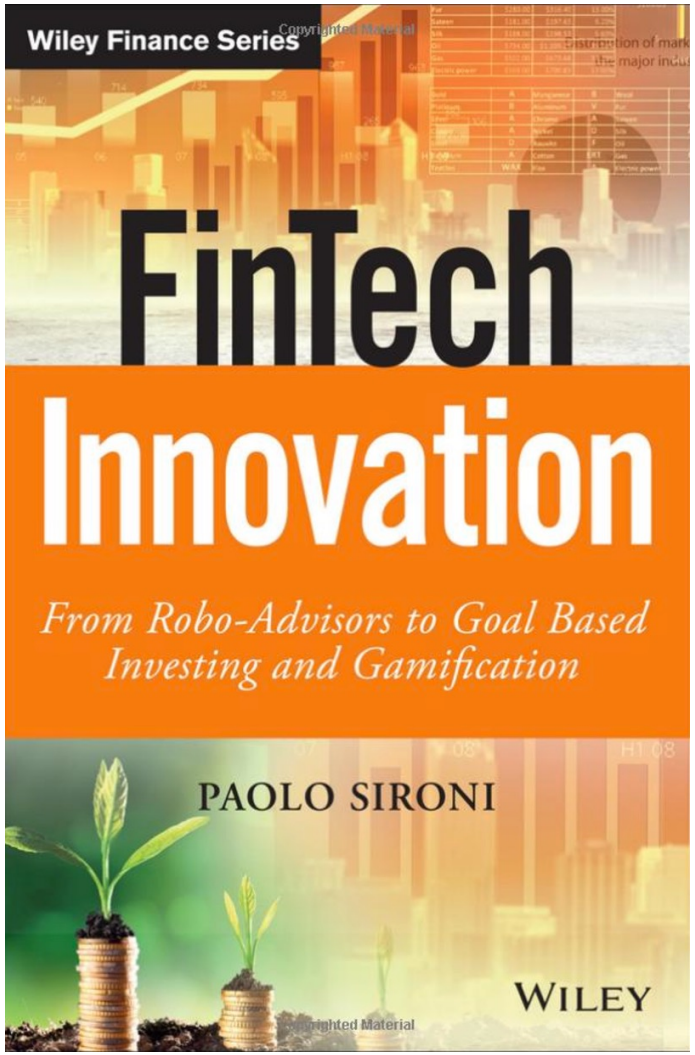



Source: https://www.amazon.com/Python-Finance-Mastering-Data-Driven/dp/1492024333

## Paolo Sironi (2016)

# FinTech Innovation:

## From Robo-Advisors to Goal Based Investing and Gamification, Wiley




Source: https://www.amazon.com/FinTech-Innovation-Robo-Advisors-Investing-Gamification/dp/1119226988

# FinTech: Financial Services Innovation


Source: http://www3.weforum.org/docs/WEF_The_future__of_financial_services.pdf

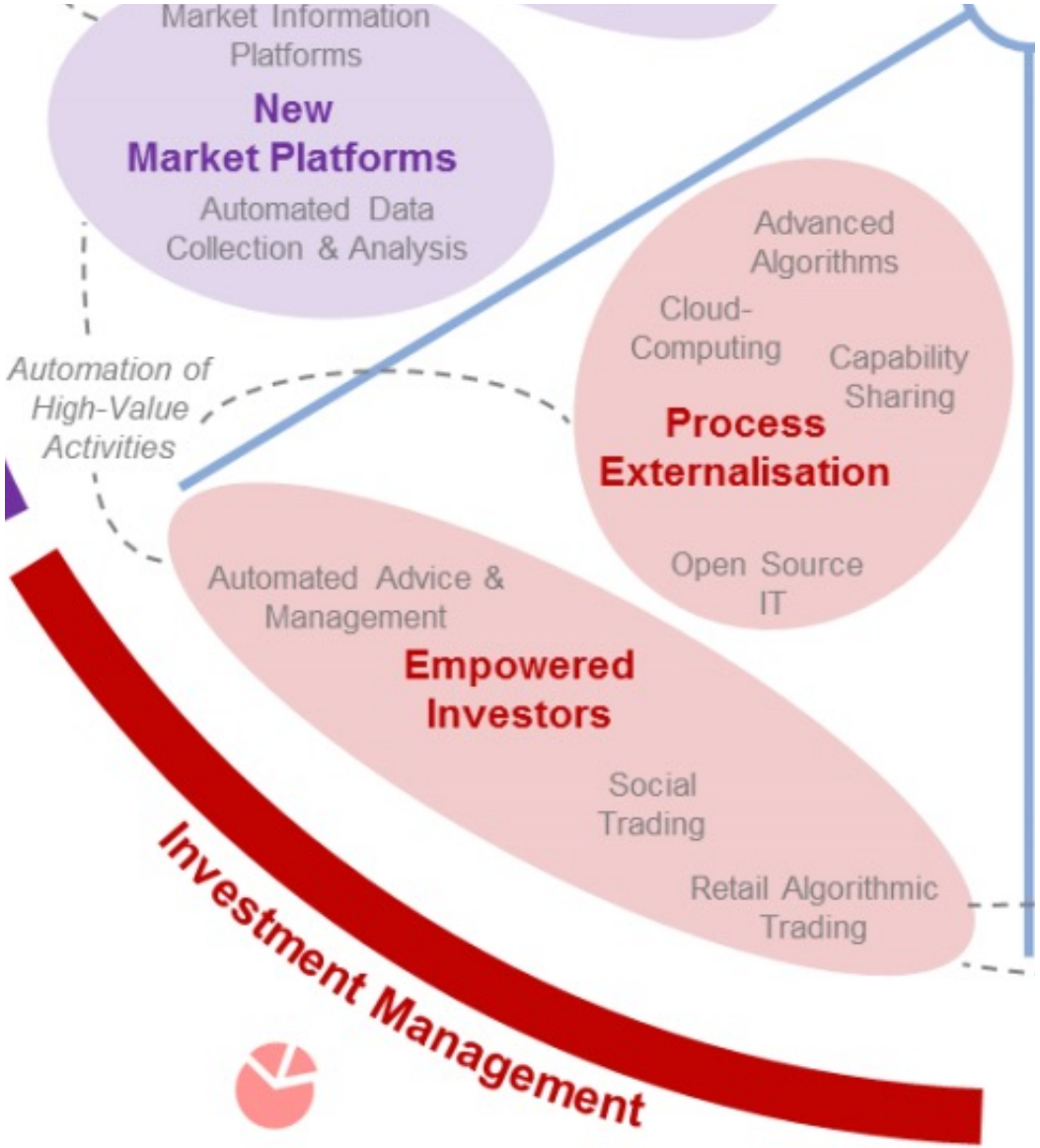
# FinTech:

## Financial Services Innovation

1. Payments
2. Insurance
3. Deposits & Lending
4. Capital Raising
5. Investment Management
6. Market Provisioning

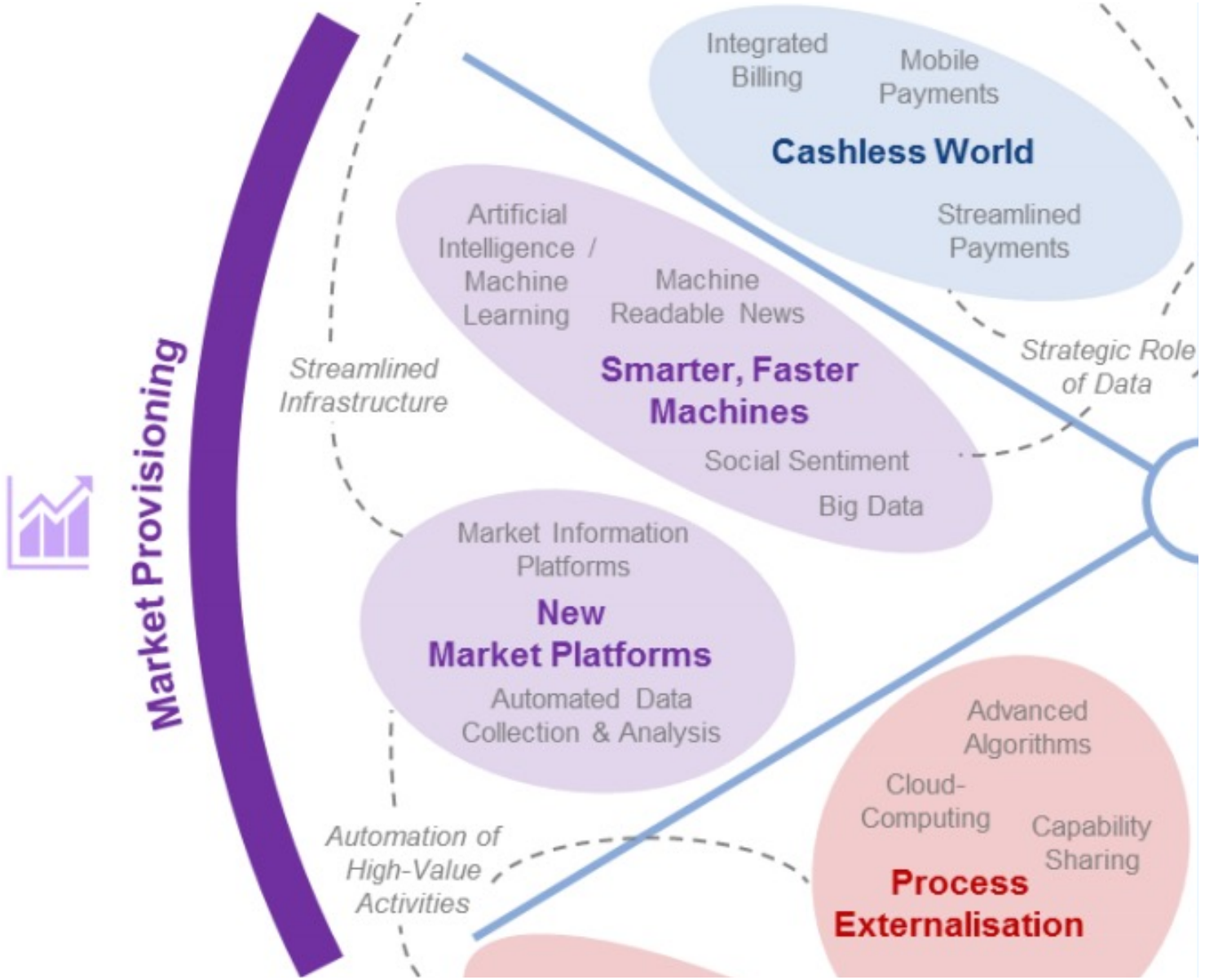
Source: http://www3.weforum.org/docs/WEF_The_future__of_financial_services.pdf

# 5 FinTech: Investment Management




Source: http://www3.weforum.org/docs/WEF_The_future__of_financial_services.pdf

# 6 FinTech: Market Provisioning




Source: http://www3.weforum.org/docs/WEF_The_future__of_financial_services.pdf

# AI in FinTech: Financial Services Innovation and Application

# FinTech ABCD

**A**I

**B**lock Chain

**C**loud Computing

Big **D**ata

# Decentralized Finance (DeFi)

## Block Chain Financial Technology

**Block Chain & Bitcoin (BTC)**

**Smart Contract & Ethereum (ETH)**

**Decentralized Application (DApp)**

# FinTech

# Financial Technology
# FinTech

**“providing financial services by making use of software and modern technology”**

Source: https://www.fintechweekly.com/fintech-definition

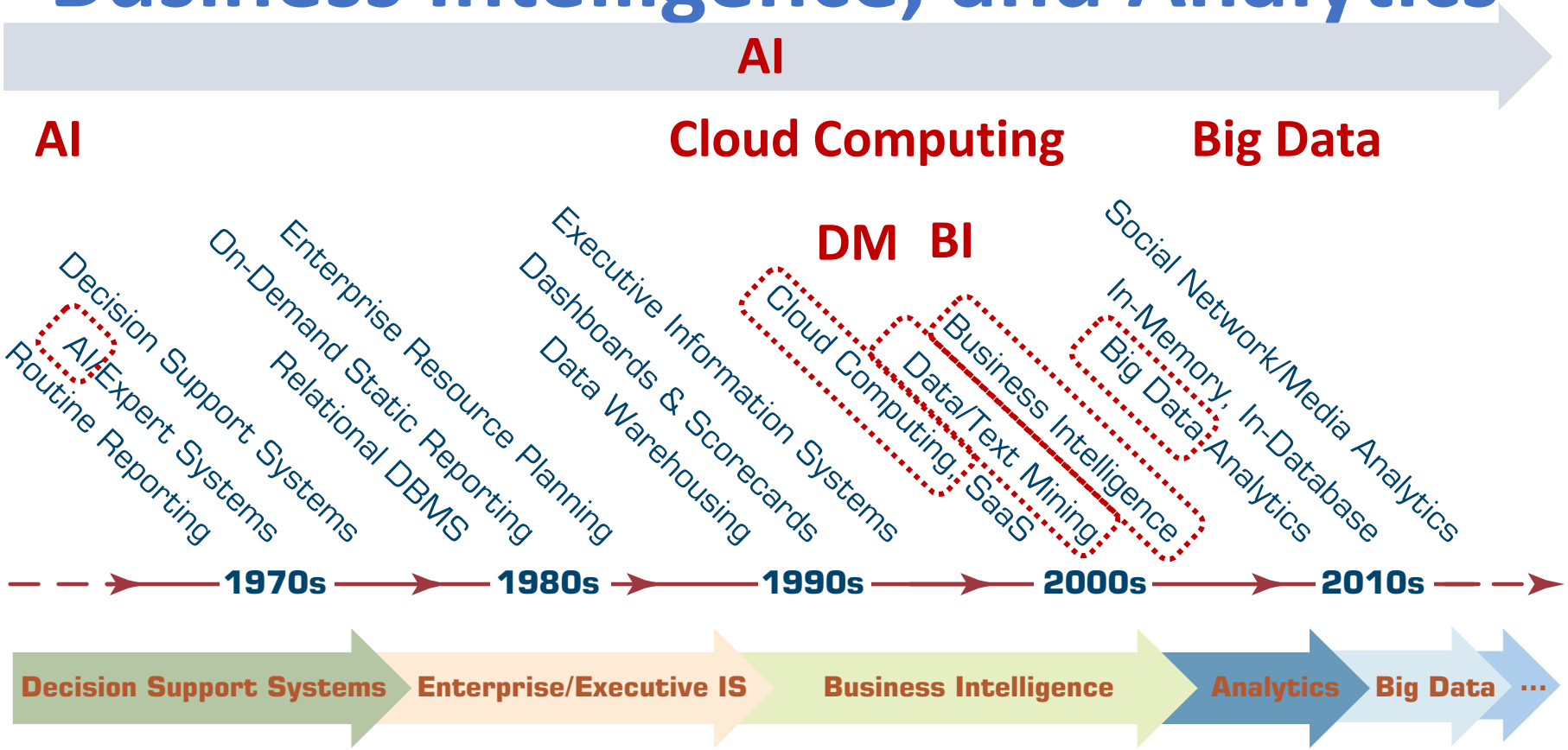
# Financial Services

# Financial Services


Source: http://www.crackitt.com/7-reasons-why-your-fintech-startup-needs-visual-marketing/

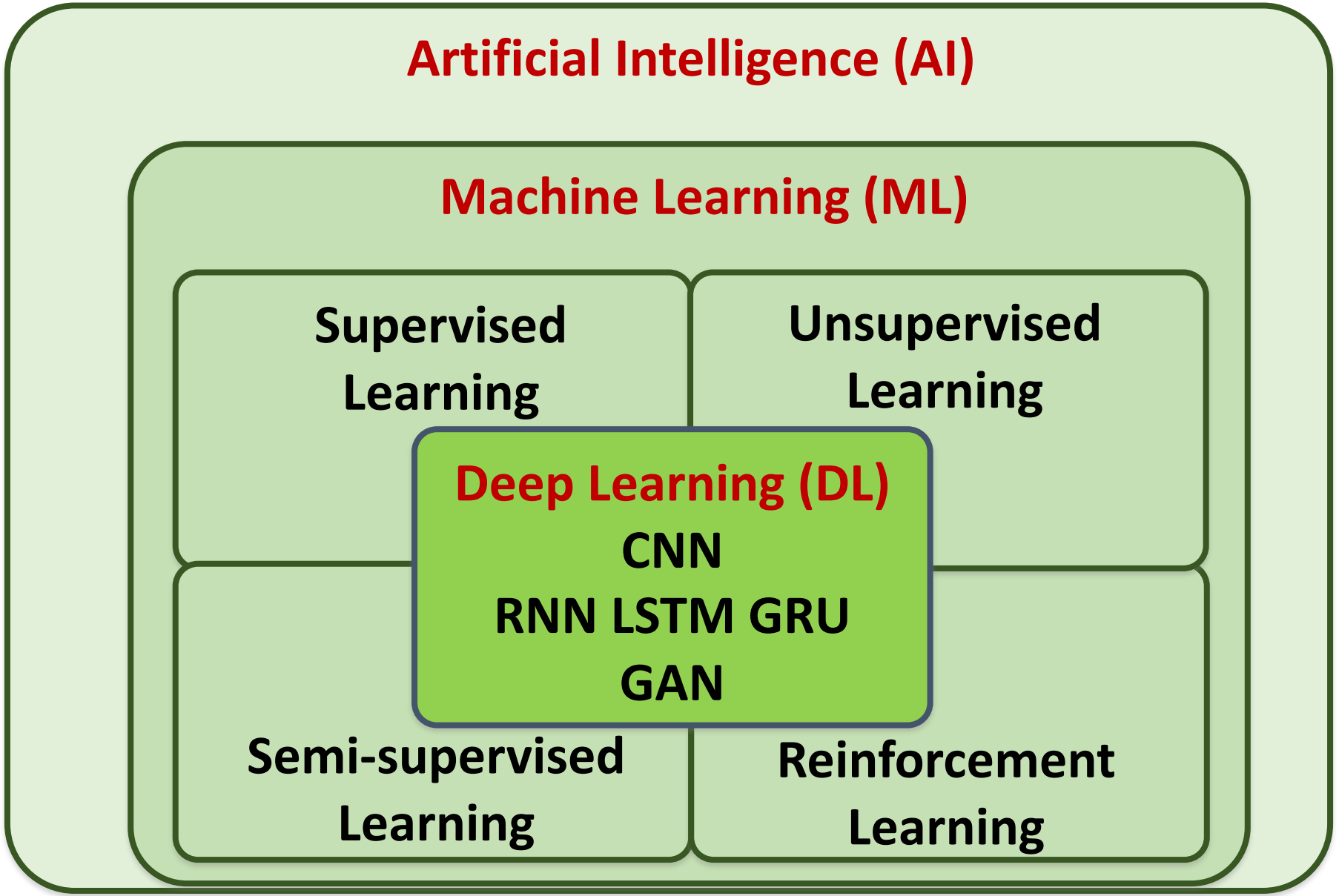
# AI, Big Data, Cloud Computing

## Evolution of Decision Support, Business Intelligence, and Analytics




Source: Ramesh Sharda, Dursun Delen, and Efraim Turban (2017),
Business Intelligence, Analytics, and Data Science: A Managerial Perspective, 4th Edition, Pearson

# AI, ML, DL




Source: https://leonardoaraujosantos.gitbooks.io/artificial-inteligence/content/deep_learning.html

# AI Acting Humanly:
# The Turing Test Approach
## (Alan Turing, 1950)

- Knowledge Representation
- Automated Reasoning
- Machine Learning (ML)
  - Deep Learning (DL)
- Computer Vision (Image, Video)
- Natural Language Processing (NLP)
- Robotics

Source: Stuart Russell and Peter Norvig (2020), Artificial Intelligence: A Modern Approach, 4th Edition, Pearson

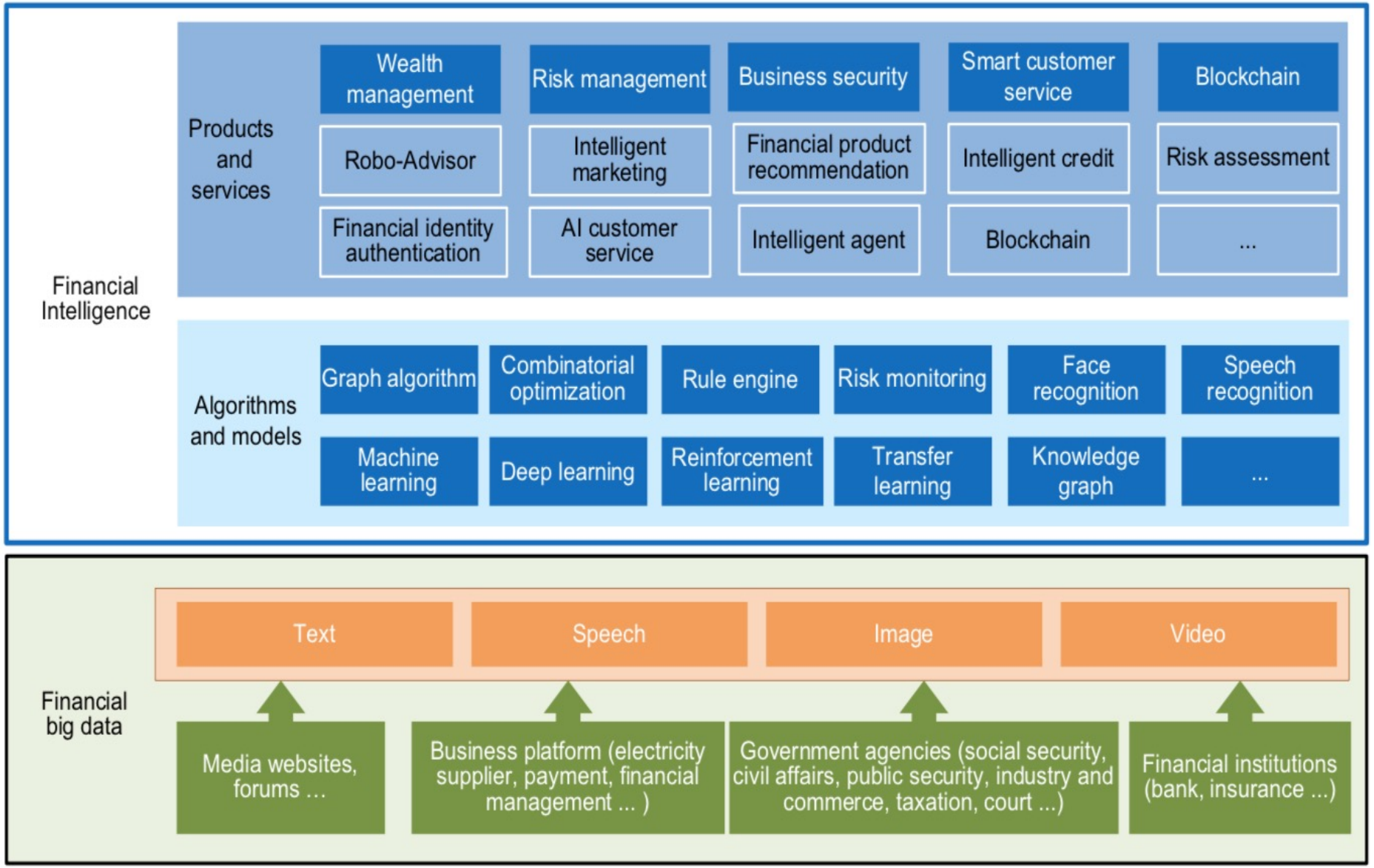
# AI

# in

# FinTech

# FinBrain: when Finance meets AI 2.0

(Zheng et al., 2019)




Source: Xiao-lin Zheng, Meng-ying Zhu, Qi-bing Li, Chao-chao Chen, and Yan-chao Tan (2019), "Finbrain: When finance meets AI 2.0." Frontiers of Information Technology & Electronic Engineering 20, no. 7, pp. 914-924

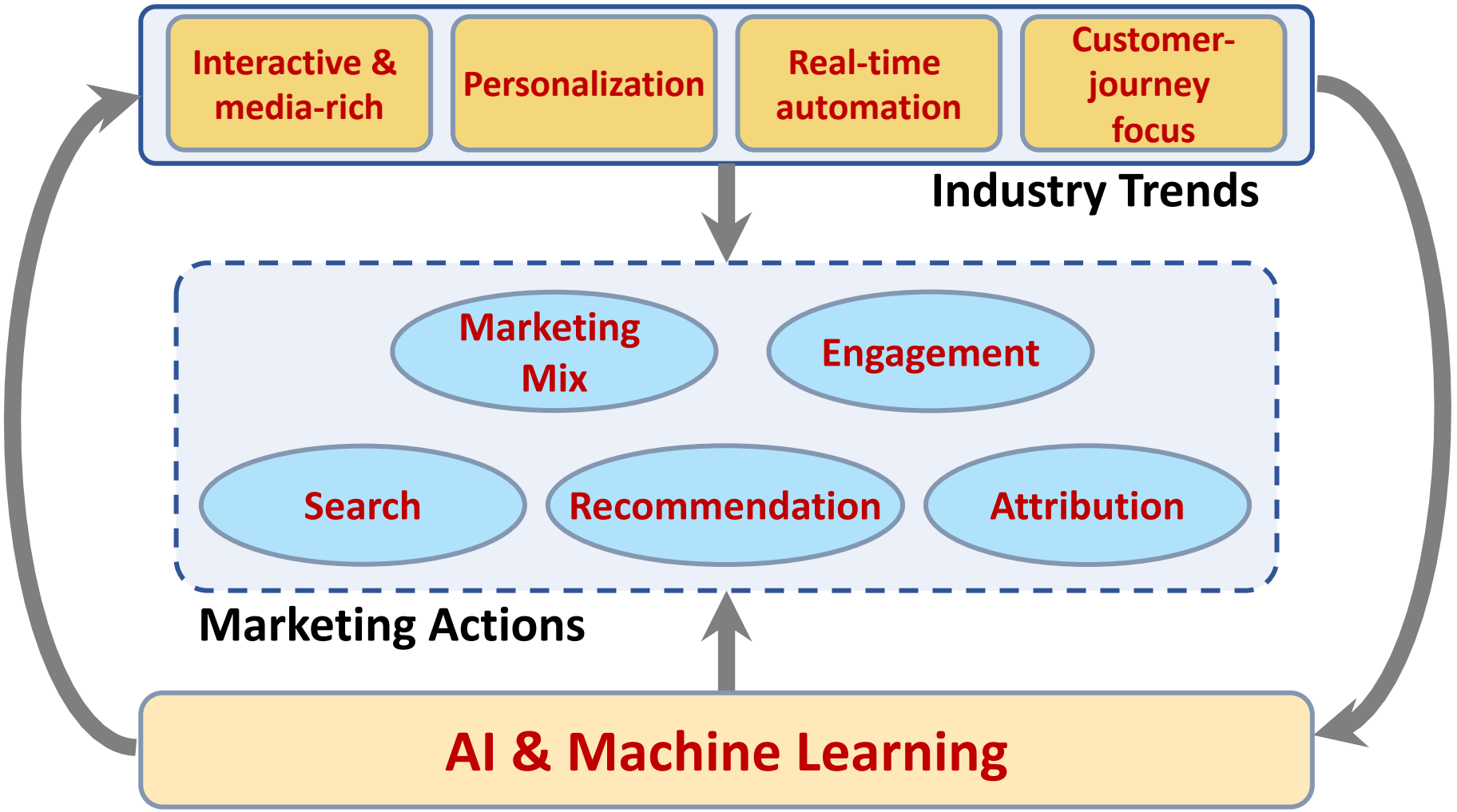
# Technology-driven Financial Industry Development

| Development stage | Driving technology | Main landscape | Inclusive finance | Relationship between technology and finance |
|---|---|---|---|---|
| Fintech 1.0 (financial IT) | Computer | Credit card, ATM, and CRMS | Low | Technology as a tool |
| Fintech 2.0 (Internet finance) | Mobile Internet | Marketplace lending, third-party payment, crowdfunding, and Internet insurance | Medium | Technology-driven change |
| Fintech 3.0 (financial intelligence) | AI, Big Data, Cloud Computing, Blockchain | Intelligent finance | High | Deep fusion |

Source: Xiao-lin Zheng, Meng-ying Zhu, Qi-bing Li, Chao-chao Chen, and Yan-chao Tan (2019), "Finbrain: When finance meets AI 2.0." Frontiers of Information Technology & Electronic Engineering 20, no. 7, pp. 914-924

# AI-driven Marketing

## (Ma and Sun, 2020)




Source: Liye Ma and Baohong Sun (2020), "Machine learning and AI in marketing – Connecting computing power to human insights." International Journal of Research in Marketing, 37, no. 3, 481-504.

# Deep learning for financial applications: A survey

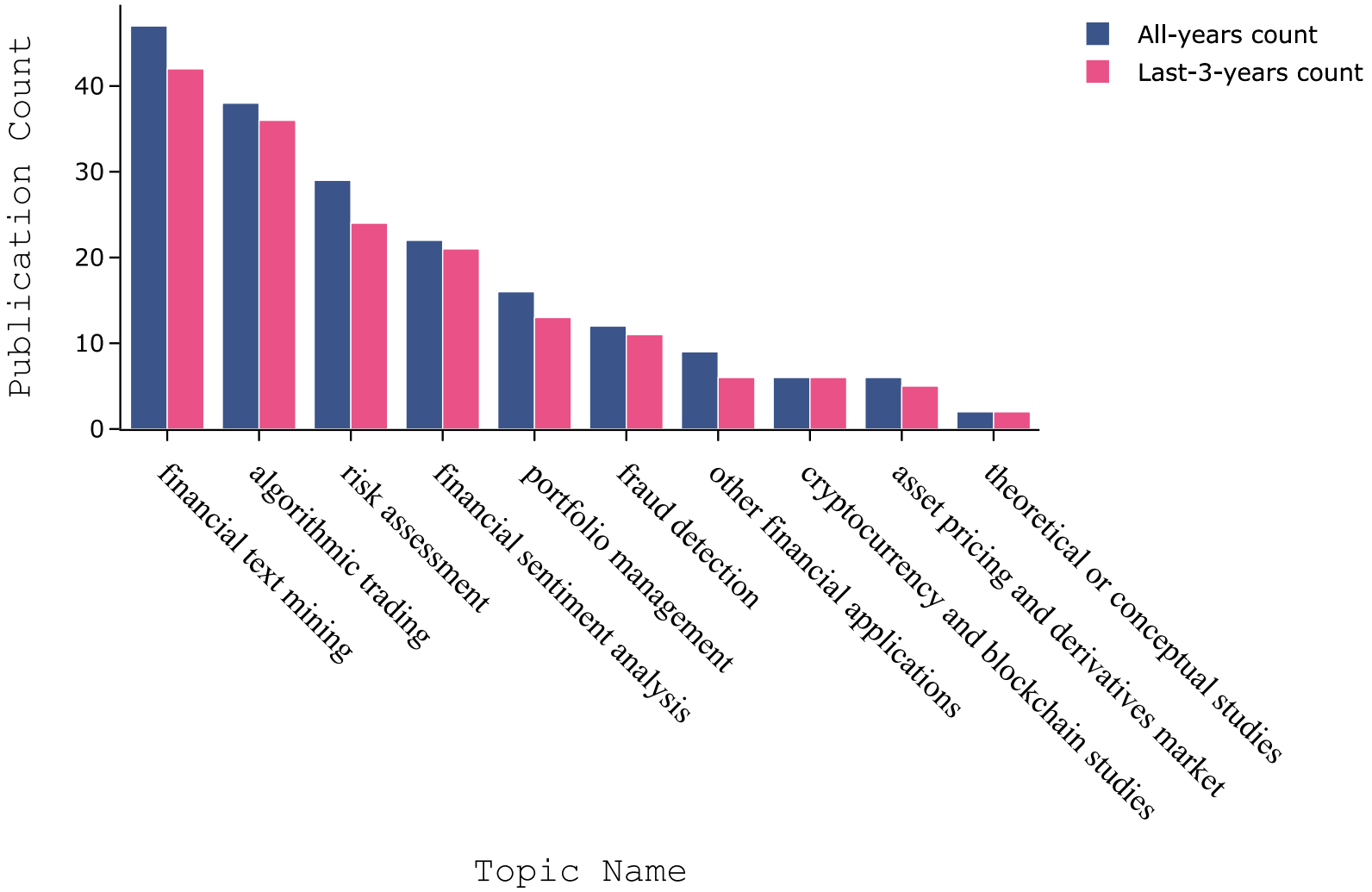
## Applied Soft Computing (2020)

Source:
Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey."
Applied Soft Computing (2020): 106384.

# Financial time series forecasting with deep learning: A systematic literature review: 2005–2019 Applied Soft Computing (2020)

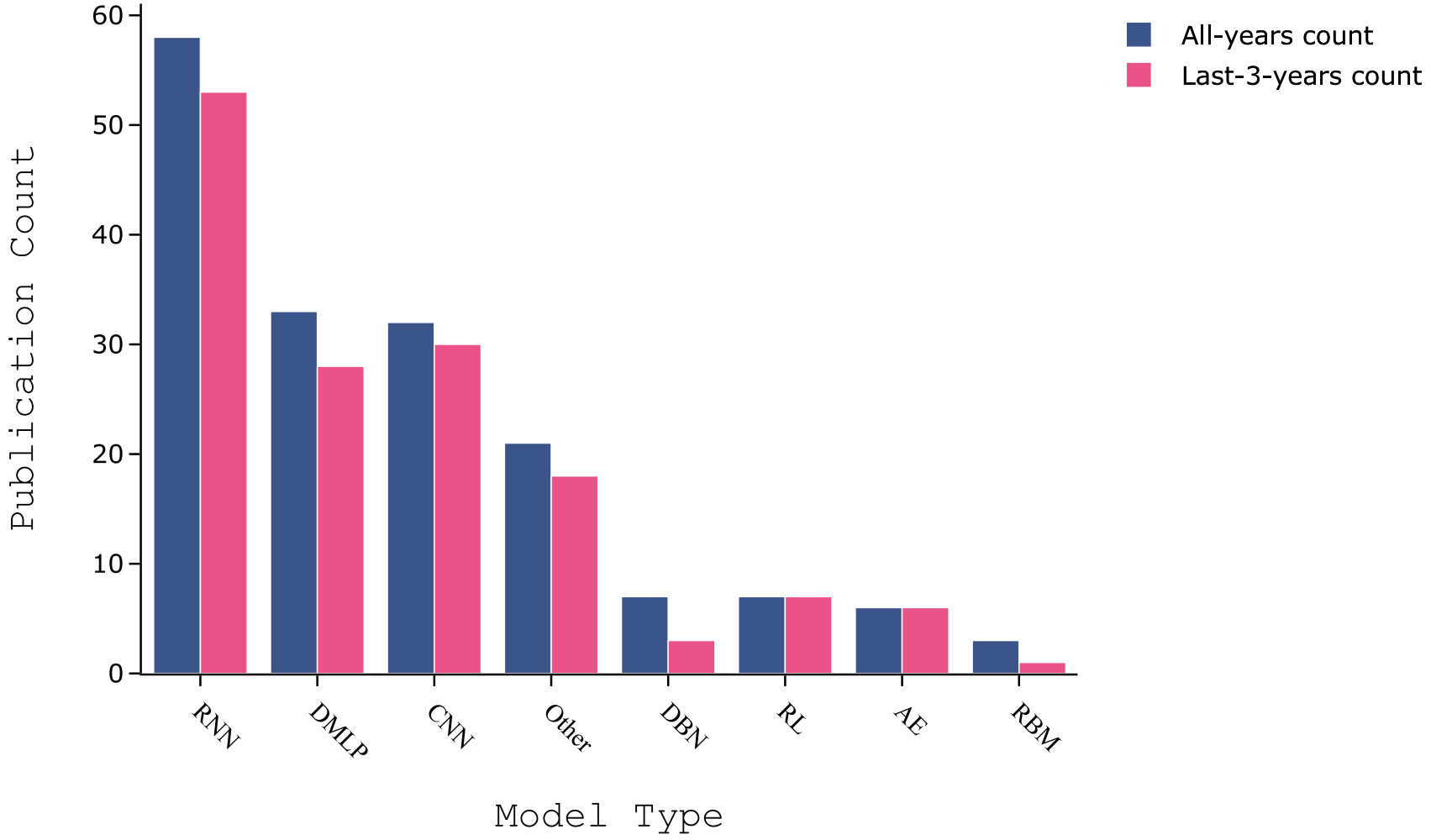
Source:
Omer Berat Sezer, Mehmet Ugur Gudelek, and Ahmet Murat Ozbayoglu (2020), "Financial time series forecasting with deep learning: A systematic literature review: 2005–2019." Applied Soft Computing 90 (2020): 106181.

# Deep learning for financial applications: Topics



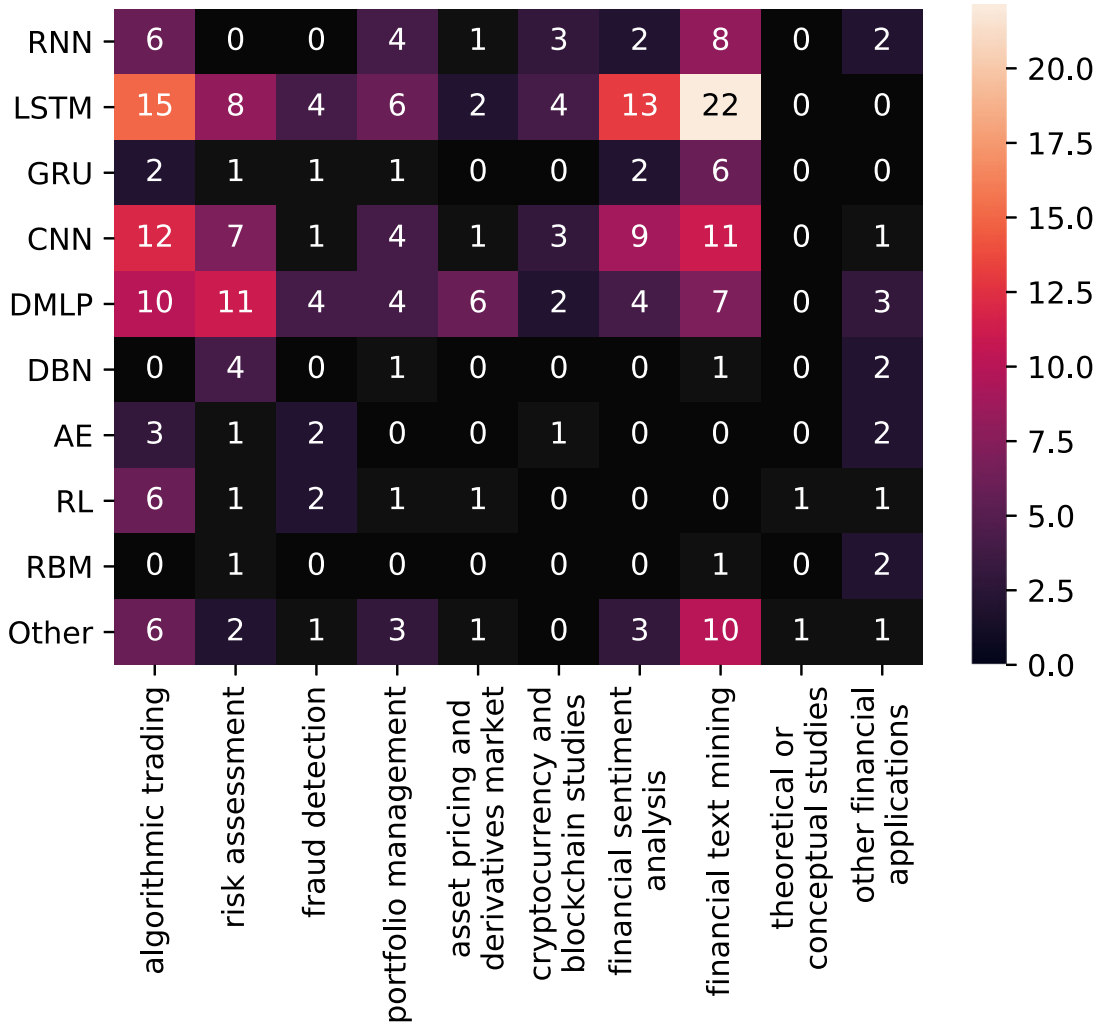

Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

# Deep learning for financial applications: Deep Learning Models



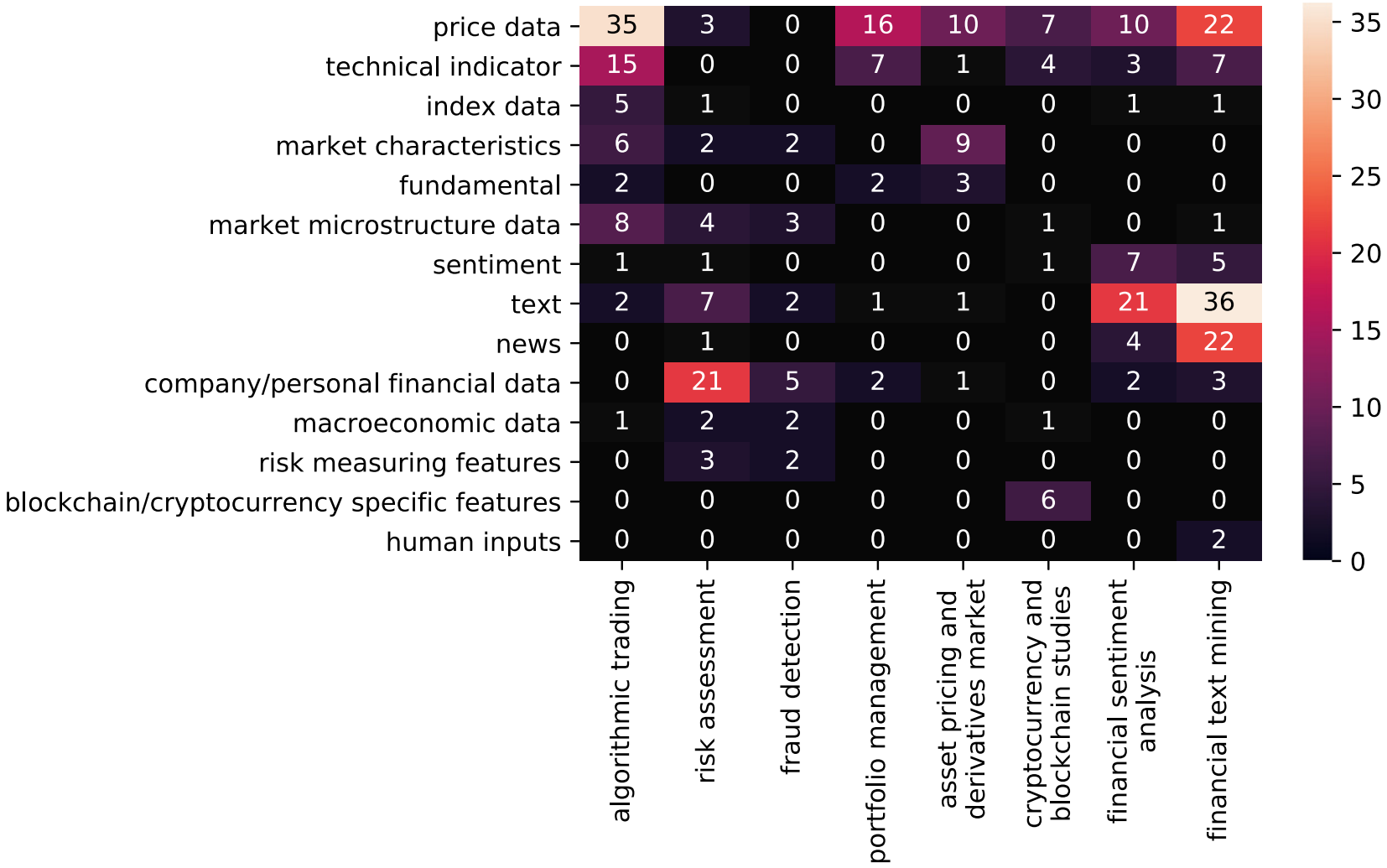

Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

# Deep learning for financial applications: Topic-Model Heatmap



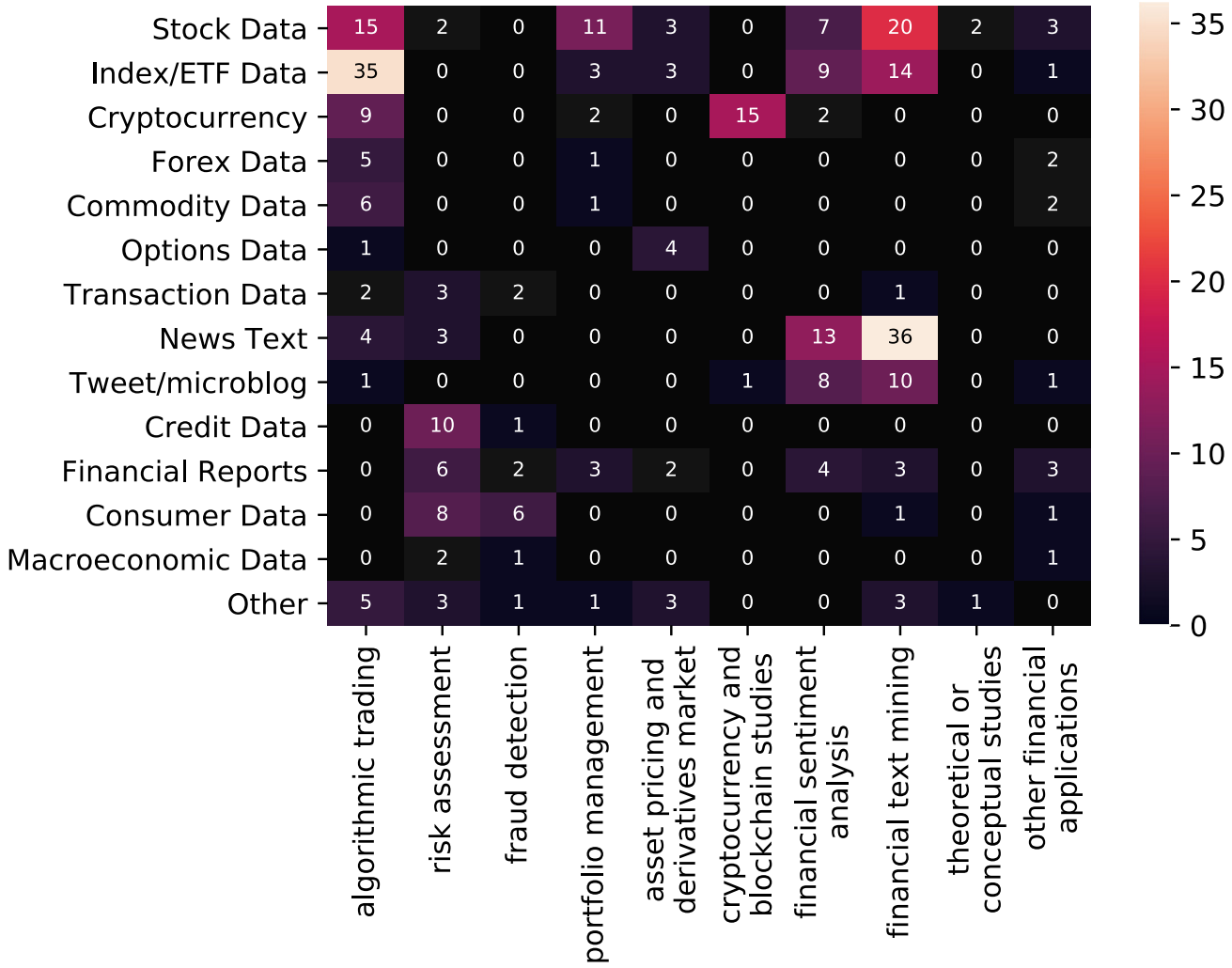

Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

# Deep learning for financial applications: Topic-Feature Heatmap




Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

# Deep learning for financial applications: Topic-Dataset Heatmap




Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

# Deep learning for financial applications:

## Algo-trading applications embedded with time series forecasting models

| Art. | Data set | Period | Feature set | Method | Performance criteria | Environment |
|---|---|---|---|---|---|---|
| [33] | GarantiBank in BIST, Turkey | 2016 | OCHLV, Spread, Volatility, Turnover, etc. | PLR, Graves LSTM | MSE, RMSE, MAE, RSE, Correlation R-square | Spark |
| [34] | CSI300, Nifty50, HSI, Nikkei 225, S&P500, DJIA | 2010–2016 | OCHLV, Technical Indicators | WT, Stacked autoencoders, LSTM | MAPE, Correlation coefficient, THEIL-U | – |
| [35] | Chinese Stocks | 2007–2017 | OCHLV | CNN + LSTM | Annualized Return, Mxm Retracement | Python |
| [36] | 50 stocks from NYSE | 2007–2016 | Price data | SFM | MSE | – |
| [37] | The LOB of 5 stocks of Finnish Stock Market | 2010 | FI-2010 dataset: bid/ask and volume | WMTR, MDA | Accuracy, Precision, Recall, F1-Score | – |
| [38] | 300 stocks from SZSE, Commodity | 2014–2015 | Price data | FDDR, DMLP+RL | Profit, return, SR, profit-loss curves | Keras |
| [39] | S&P500 Index | 1989–2005 | Price data, Volume | LSTM | Return, STD, SR, Accuracy | Python, TensorFlow, Keras, R, H2O |
| [40] | Stock of National Bank of Greece (ETE). | 2009–2014 | FTSE100, DJIA, GDAX, NIKKEI225, EUR/USD, Gold | GASVR, LSTM | Return, volatility, SR, Accuracy | Tensorflow |
| [41] | Chinese stock-IF-IH-IC contract | 2016–2017 | Decisions for price change | MODRL+LSTM | Profit and loss, SR | – |
| [42] | Singapore Stock Market Index | 2010–2017 | OCHL of last 10 days of Index | DMLP | RMSE, MAPE, Profit, SR | – |
| [43] | GBP/USD | 2017 | Price data | Reinforcement Learning + LSTM + NES | SR, downside deviation ratio, total profit | Python, Keras, Tensorflow |
| [44] | Commodity, FX future, ETF | 1991–2014 | Price Data | DMLP | SR, capability ratio, return | C++, Python |
| [45] | USD/GBP, S&P500, FTSE100, oil, gold | 2016 | Price data | AE + CNN | SR, % volatility, avg return/trans, rate of return | H2O |

Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

# Deep learning for financial applications:

## Algo-trading applications embedded with time series forecasting models

| Art. | Data set | Period | Feature set | Method | Performance criteria | Environment |
|---|---|---|---|---|---|---|
| | | | | | rate of return | |
| [46] | Bitcoin, Dash, Ripple, Monero, Litecoin, Dogecoin, Nxt, Namecoin | 2014–2017 | MA, BOLL, the CRIX returns, Euribor interest rates, OCHLV | LSTM, RNN, DMLP | Accuracy, F1-measure | Python, Tensorflow |
| [47] | S&P500, KOSPI, HSI, and EuroStoxx50 | 1987–2017 | 200-days stock price | Deep Q-Learning, DMLP | Total profit, Correlation | – |
| [48] | Stocks in the S&P500 | 1990–2015 | Price data | DMLP, GBT, RF | Mean return, MDD, Calmar ratio | H2O |
| [49] | Fundamental and Technical Data, Economic Data | – | Fundamental , technical and market information | CNN | – | – |

Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

# Deep learning for financial applications:

## Classification (buy–sell signal, or trend detection) based algo-trading models

| Art. | Data set | Period | Feature set | Method | Performance criteria | Environment |
|---|---|---|---|---|---|---|
| [51] | Stocks in Dow30 | 1997–2017 | RSI | DMLP with genetic algorithm | Annualized return | Spark MLlib, Java |
| [52] | SPY ETF, 10 stocks from S&P500 | 2014–2016 | Price data | FFNN | Cumulative gain | MatConvNet, Matlab |
| [53] | Dow30 stocks | 2012–2016 | Close data and several technical indicators | LSTM | Accuracy | Python, Keras, Tensorflow, TALIB |
| [54] | High-frequency record of all orders | 2014–2017 | Price data, record of all orders, transactions | LSTM | Accuracy | – |
| [55] | Nasdaq Nordic (Kesko Oyj, Outokumpu Oyj, Sampo, Rautaruukki, Wartsila Oyj) | 2010 | Price and volume data in LOB | LSTM | Precision, Recall, F1-score, Cohen's k | – |
| [56] | 17 ETFs | 2000–2016 | Price data, technical indicators | CNN | Accuracy, MSE, Profit, AUROC | Keras, Tensorflow |
| [57] | Stocks in Dow30 and 9 Top Volume ETFs | 1997–2017 | Price data, technical indicators | CNN with feature imaging | Recall, precision, F1-score, annualized return | Python, Keras, Tensorflow, Java |
| [58] | FTSE100 | 2000–2017 | Price data | CAE | TR, SR, MDD, mean return | – |
| [59] | Nasdaq Nordic (Kesko Oyj, Outokumpu Oyj, Sampo, Rautaruukki, Wartsila Oyj) | 2010 | Price, Volume data, 10 orders of the LOB | CNN | Precision, Recall, F1-score, Cohen's k | Theano, Scikit learn, Python |
| [60] | Borsa Istanbul 100 Stocks | 2011–2015 | 75 technical indicators and OCHLV | CNN | Accuracy | Keras |
| [61] | ETFs and Dow30 | 1997–2007 | Price data | CNN with feature imaging | Annualized return | Keras, Tensorflow |
| [62] | 8 experimental assets from bond/derivative market | – | Asset prices data | RL, DMLP, Genetic Algorithm | Learning and genetic algorithm error | – |
| [63] | 10 stocks from S&P500 | – | Stock Prices | TDNN, RNN, PNN | Missed opportunities, false alarms ratio | – |
| [64] | London Stock Exchange | 2007–2008 | Limit order book state, trades, buy/sell orders, order deletions | CNN | Accuracy, kappa | Caffe |
| [65] | Cryptocurrencies, Bitcoin | 2014–2017 | Price data | CNN, RNN, LSTM | Accumulative portfolio value, MDD, SR | – |

Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

# Deep learning for financial applications:

## Stand-alone and/or other algorithmic models

| Art. | Data set | Period | Feature set | Method | Performance criteria | Environment |
|---|---|---|---|---|---|---|
| [66] | DAX, FTSE100, call/put options | 1991–1998 | Price data | Markov model, RNN | Ewa-measure, iv, daily profits' mean and std | – |
| [67] | Taiwan Stock Index Futures, Mini Index Futures | 2012–2014 | Price data to image | Visualization method + CNN | Accumulated profits,accuracy | – |
| [68] | Energy-Sector/ Company-Centric Tweets in S&P500 | 2015–2016 | Text and Price data | LSTM, RNN, GRU | Return, SR, precision, recall, accuracy | Python, Tweepy API |
| [69] | CME FIX message | 2016 | Limit order book, time-stamp, price data | RNN | Precision, recall, F1-measure | Python, TensorFlow, R |
| [70] | Taiwan stock index futures (TAIFEX) | 2017 | Price data | Agent based RL with CNN pre-trained | Accuracy | – |
| [71] | Stocks from S&P500 | 2010–2016 | OCHLV | DCNL | PCC, DTW, VWL | Pytorch |
| [72] | News from NowNews, AppleDaily, LTN, MoneyDJ for 18 stocks | 2013–2014 | Text, Sentiment | DMLP | Return | Python, Tensorflow |
| [73] | 489 stocks from S&P500 and NASDAQ-100 | 2014–2015 | Limit Order Book | Spatial neural network | Cross entropy error | NVIDIA's cuDNN |
| [74] | Experimental dataset | – | Price data | DRL with CNN, LSTM, GRU, DMLP | Mean profit | Python |

Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

# Deep learning for financial applications:
# Credit scoring or classification studies

| Art. | Data set | Period | Feature set | Method | Performance criteria | Env. |
|---|---|---|---|---|---|---|
| [77] | The XR 14 CDS contracts | 2016 | Recovery rate, spreads, sector and region | DBN+RBM | AUROC, FN, FP, Accuracy | WEKA |
| [78] | German, Japanese credit datasets | – | Personal financial variables | SVM + DBN | Weighted-accuracy, TP, TN | – |
| [79] | Credit data from Kaggle | – | Personal financial variables | DMLP | Accuracy, TP, TN, G-mean | – |
| [80] | Australian, German credit data | – | Personal financial variables | GP + AE as Boosted DMLP | FP | Python, Scikit-learn |
| [81] | German, Australian credit dataset | – | Personal financial variables | DCNN, DMLP | Accuracy, False/Missed alarm | – |
| [82] | Consumer credit data from Chinese finance company | – | Relief algorithm chose the 50 most important features | CNN + Relief | AUROC, K-s statistic, Accuracy | Keras |
| [83] | Credit approval dataset by UCI Machine Learning repo | – | UCI credit approval dataset | Rectifier, Tanh, Maxout DL | – | AWS EC2, H2O, R |

Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

# Deep learning for financial applications:

## Financial distress, bankruptcy, bank risk, mortgage risk, crisis forecasting studies.

| Art. | Data set | Period | Feature set | Method | Performance criteria | Env. |
|---|---|---|---|---|---|---|
| [84] | 966 french firms | – | Financial ratios | RBM+SVM | Precision, Recall | – |
| [85] | 883 BHC from EDGAR | 2006–2017 | Tokens, weighted sentiment polarity, leverage and ROA | CNN, LSTM, SVM, RF | Accuracy, Precision, Recall, F1-score | Keras, Python, Scikit-learn |
| [86] | The event data set for large European banks, news articles from Reuters | 2007–2014 | Word, sentence | DMLP +NLP preprocess | Relative usefulness, F1-score | – |
| [87] | Event dataset on European banks, news from Reuters | 2007–2014 | Text, sentence | Sentence vector + DFFN | Usefulness, F1-score, AUROC | – |
| [88] | News from Reuters, fundamental data | 2007–2014 | Financial ratios and news text | doc2vec + NN | Relative usefulness | Doc2vec |
| [89] | Macro/Micro economic variables, Bank characteristics/performance variables from BHC | 1976–2017 | Macro economic variables and bank performances | CGAN, MVN, MV-t, LSTM, VAR, FE-QAR | RMSE, Log likelihood, Loan loss rate | – |
| [90] | Financial statements of French companies | 2002–2006 | Financial ratios | DBN | Recall, Precision, F1-score, FP, FN | – |
| [91] | Stock returns of American publicly-traded companies from CRSP | 2001–2011 | Price data | DBN | Accuracy | Python, Theano |
| [92] | Financial statements of several companies from Japanese stock market | 2002–2016 | Financial ratios | CNN | F1-score, AUROC | – |
| [93] | Mortgage dataset with local and national economic factors | 1995–2014 | Mortgage related features | DMLP | Negative average log-likelihood | AWS |
| [94] | Mortgage data from Norwegian financial service group, DNB | 2012–2016 | Personal financial variables | CNN | Accuracy, Sensitivity, Specificity, AUROC | – |
| [95] | Private brokerage company's real data of risky transactions | – | 250 features: order details, etc. | CNN, LSTM | F1-Score | Keras, Tensorflow |
| [96] | Several datasets combined to create a new one | 1996–2017 | Index data, 10-year Bond yield, exchange rates, | Logit, CART, RF, SVM, NN, XGBoost, DMLP | AUROC, KS, G-mean, likelihood ratio, DP, BA, WBA | R |

Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

# Deep learning for financial applications:

# Fraud detection studies

| Art. | Data set | Period | Feature set | Method | Performance criteria | Env. |
|---|---|---|---|---|---|---|
| [114] | Debit card transactions by a local Indonesia bank | 2016–2017 | Financial transaction amount on several time periods | CNN, Stacked-LSTM, CNN-LSTM | AUROC | – |
| [115] | Credit card transactions from retail banking | 2017 | Transaction variables and several derived features | LSTM, GRU | Accuracy | Keras |
| [116] | Card purchases' transactions | 2014–2015 | Probability of fraud per currency/origin country, other fraud related features | DMLP | AUROC | – |
| [117] | Transactions made with credit cards by European cardholders | 2013 | Personal financial variables to PCA | DMLP, RF | Recall, Precision, Accuracy | – |
| [118] | Credit-card transactions | 2015 | Transaction and bank features | LSTM | AUROC | Keras, Scikit-learn |
| [119] | Databases of foreign trade of the Secretariat of Federal Revenue of Brazil | 2014 | 8 Features: Foreign Trade, Tax, Transactions, Employees, Invoices, etc | AE | MSE | H2O, R |
| [120] | Chamber of Deputies open data, Companies data from Secretariat of Federal Revenue of Brazil | 2009–2017 | 21 features: Brazilian State expense, party name, Type of expense, etc. | Deep Autoencoders | MSE, RMSE | H2O, R |
| [121] | Real-world data for automobile insurance company labeled as fradulent | – | Car, insurance and accident related features | DMLP + LDA | TP, FP, Accuracy, Precision, F1-score | – |
| [122] | Transactions from a giant online payment platform | 2006 | Personal financial variables | GBDT+DMLP | AUROC | – |
| [123] | Financial transactions | – | Transaction data | LSTM | t-SNE | – |
| [124] | Empirical data from Greek firms | – | – | DQL | Revenue | Torch |

Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

# Deep learning for financial applications:

# Portfolio management studies

| Art. | Data set | Period | Feature set | Method | Performance criteria | Env. |
|---|---|---|---|---|---|---|
| [65] | Cryptocurrencies, Bitcoin | 2014–2017 | Price data | CNN, RNN, LSTM | Accumulative portfolio value, MDD, SR | – |
| [127] | Stocks from NYSE, AMEX, NASDAQ | 1965–2009 | Price data | Autoencoder + RBM | Accuracy, confusion matrix | – |
| [128] | 20 stocks from S&P500 | 2012–2015 | Technical indicators | DMLP | Accuracy | Python, Scikit Learn, Keras, Theano |
| [129] | Chinese stock data | 2012–2013 | Technical, fundamental data | Logistic Regression, RF, DMLP | AUC, accuracy, precision, recall, f1, tpr, fpr | Keras, Tensorflow, Python, Scikit learn |
| [130] | Top 5 companies in S&P500 | – | Price data and Financial ratios | LSTM, Auto-encoding, Smart indexing | CAGR | – |
| [131] | IBB biotechnology index, stocks | 2012–2016 | Price data | Auto-encoding, Calibrating, Validating, Verifying | Returns | – |
| [132] | Taiwans stock market | – | Price data | Elman RNN | MSE, return | – |
| [133] | FOREX (EUR/USD, etc.), Gold | 2013 | Price data | Evolino RNN | Return | Python |
| [134] | Stocks in NYSE, AMEX, NASDAQ, TAQ intraday trade | 1993–2017 | Price, 15 firm characteristics | LSTM+DMLP | Monthly return, SR | Python,Keras, Tensorflow in AWS |
| [135] | S&P500 | 1985–2006 | monthly and daily log-returns | DBN+MLP | Validation, Test Error | Theano, Python, Matlab |
| [136] | 10 stocks in S&P500 | 1997–2016 | OCHLV, Price data | RNN, LSTM, GRU | Accuracy, Monthly return | Keras, Tensorflow |
| [137] | Analyst reports on the TSE and Osaka Exchange | 2016–2018 | Text | LSTM, CNN, Bi-LSTM | Accuracy, $R^2$ | R, Python, MeCab |
| [138] | Stocks from Chinese/American stock market | 2015–2018 | OCHLV, Fundamental data | DDPG, PPO | SR, MDD | – |
| [139] | Hedge fund monthly return data | 1996–2015 | Return, SR, STD, Skewness, Kurtosis, Omega ratio, Fund alpha | DMLP | Sharpe ratio, Annual return, Cum. return | – |
| [140] | 12 most-volumed cryptocurrency | 2015–2016 | Price data | CNN + RL | SR, portfolio value, MDD | – |

Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

# Deep learning for financial applications:

## Asset pricing and derivatives market studies

| Art. | Der. type | Data set | Period | Feature set | Method | Performance criteria | Env. |
|---|---|---|---|---|---|---|---|
| [137] | Asset pricing | Analyst reports on the TSE and Osaka Exchange | 2016–2018 | Text | LSTM, CNN, Bi-LSTM | Accuracy, $R^2$ | R, Python, MeCab |
| [142] | Options | Simulated a range of call option prices | – | Price data, option strike/maturity, dividend/risk free rates, volatility | DMLP | RMSE, the average percentage pricing error | Tensorflow |
| [143] | Futures, Options | TAIEX Options | 2017 | OCHLV, fundamental analysis, option price | DMLP, DMLP with Black scholes | RMSE, MAE, MAPE | – |
| [144] | Equity returns | Returns in NYSE, AMEX, NASDAQ | 1975–2017 | 57 firm characteristics | Fama–French n-factor model DL | $R^2$,RMSE | Tensorflow |

Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

# Deep learning for financial applications:
## Cryptocurrency and blockchain studies

| Art. | Data set | Period | Feature set | Method | Performance criteria | Env. |
|---|---|---|---|---|---|---|
| [46] | Bitcoin, Dash, Ripple, Monero, Litecoin, Dogecoin, Nxt, Namecoin | 2014–2017 | MA, BOLL, the CRIX daily returns, Euribor interest rates, OCHLV of EURO/UK, EURO/USD, US/JPY | LSTM, RNN, DMLP | Accuracy, F1-measure | Python, Tensorflow |
| [65] | Cryptocurrencies, Bitcoin | 2014–2017 | Price data | CNN | Accumulative portfolio value, MDD, SR | – |
| [140] | 12 most-volumed cryptocurrency | 2015–2016 | Price data | CNN + RL | SR, portfolio value, MDD | |
| [145] | Bitcoin data | 2010–2017 | Hash value, bitcoin address, public/private key, digital signature, etc. | Takagi–Sugeno Fuzzy cognitive maps | Analytical hierarchy process | – |
| [146] | Bitcoin data | 2012, 2013, 2016 | TransactionId, input/output Addresses, timestamp | Graph embedding using heuristic, laplacian eigen-map, deep AE | F1-score | – |
| [147] | Bitcoin, Litecoin, StockTwits | 2015–2018 | OCHLV, technical indicators, sentiment analysis | CNN, LSTM, State Frequency Model | MSE | Keras, Tensorflow |
| [148] | Bitcoin | 2013–2016 | Price data | Bayesian optimized RNN, LSTM | Sensitivity, specificity, precision, accuracy, RMSE | Keras, Python, Hyperas |

Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

# Deep learning for financial applications:

## Financial sentiment studies coupled with text mining for forecasting

| Art. | Data set | Period | Feature set | Method | Performance criteria | Env. |
|---|---|---|---|---|---|---|
| [137] | Analyst reports on the TSE and Osaka Exchange | 2016–2018 | Text | LSTM, CNN, Bi-LSTM | Accuracy, $R^2$ | R, Python, MeCab |
| [150] | Sina Weibo, Stock market records | 2012–2015 | Technical indicators, sentences | DRSE | F1-score, precision, recall, accuracy, AUROC | Python |
| [151] | News from Reuters and Bloomberg for S&P500 stocks | 2006–2015 | Financial news, price data | DeepClue | Accuracy | Dynet software |
| [152] | News from Reuters and Bloomberg, Historical stock security data | 2006–2013 | News, price data | DMLP | Accuracy | – |
| [153] | SCI prices | 2008–2015 | OCHL of change rate, price | Emotional Analysis + LSTM | MSE | – |
| [154] | SCI prices | 2013–2016 | Text data and Price data | LSTM | Accuracy, F1-Measure | Python, Keras |
| [155] | Stocks of Google, Microsoft and Apple | 2016–2017 | Twitter sentiment and stock prices | RNN | – | Spark, Flume,Twitter API, |
| [156] | 30 DJIA stocks, S&P500, DJI, news from Reuters | 2002–2016 | Price data and features from news articles | LSTM, NN, CNN and word2vec | Accuracy | VADER |
| [157] | Stocks of CSI300 index, OCHLV of CSI300 index | 2009–2014 | Sentiment Posts, Price data | Naive Bayes + LSTM | Precision, Recall, F1-score, Accuracy | Python, Keras |
| [158] | S&P500, NYSE Composite, DJIA, NASDAQ Composite | 2009–2011 | Twitter moods, index data | DNN, CNN | Error rate | Keras, Theano |

Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

# Deep learning for financial applications:

## Text mining studies without sentiment analysis for forecasting

| Art. | Data set | Period | Feature set | Method | Performance criteria | Env. |
|---|---|---|---|---|---|---|
| [68] | Energy-Sector/ Company-Centric Tweets in S&P500 | 2015–2016 | Text and Price data | RNN, KNN, SVR, LinR | Return, SR, precision, recall, accuracy | Python, Tweepy API |
| [165] | News from Reuters, Bloomberg | 2006–2013 | Financial news, price data | Bi-GRU | Accuracy | Python, Keras |
| [166] | News from Sina.com, ACE2005 Chinese corpus | 2012–2016 | A set of news text | Their unique algorithm | Precision, Recall, F1-score | – |
| [167] | CDAX stock market data | 2010–2013 | Financial news, stock market data | LSTM | MSE, RMSE, MAE, Accuracy, AUC | TensorFlow, Theano, Python, Scikit-Learn |
| [168] | Apple, Airbus, Amazon news from Reuters, Bloomberg, S&P500 stock prices | 2006–2013 | Price data, news, technical indicators | TGRU, stock2vec | Accuracy, precision, AUROC | Keras, Python |
| [169] | S&P500 Index, 15 stocks in S&P500 | 2006–2013 | News from Reuters and Bloomberg | CNN | Accuracy, MCC | – |
| [170] | S&P500 index news from Reuters | 2006–2013 | Financial news titles, Technical indicators | SI-RCNN (LSTM + CNN) | Accuracy | – |
| [171] | 10 stocks in Nikkei 225 and news | 2001–2008 | Textual information and Stock prices | Paragraph Vector + LSTM | Profit | – |
| [172] | NIFTY50 Index, NIFTY Bank/Auto/IT/Energy Index, News | 2013–2017 | Index data, news | LSTM | MCC, Accuracy | – |
| [173] | Price data, index data, news, social media data | 2015 | Price data, news from articles and social media | Coupled matrix and tensor | Accuracy, MCC | Jieba |
| [174] | HS300 | 2015–2017 | Social media news, price data | RNN-Boost with LDA | Accuracy, MAE, MAPE, RMSE | Python, Scikit-learn |

Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

# Deep learning for financial applications:

## Text mining studies without sentiment analysis for forecasting

| Art. | Data set | Period | Feature set | Method | Performance criteria | Env. |
|---|---|---|---|---|---|---|
| [175] | News and Chinese stock data | 2014–2017 | Selected words in a news | HAN | Accuracy, Annual return | – |
| [176] | News, stock prices from Hong Kong Stock Exchange | 2001 | Price data and TF-IDF from news | ELM, DLR, PCA, BELM, KELM, NN | Accuracy | Matlab |
| [177] | TWSE index, 4 stocks in TWSE | 2001–2017 | Technical indicators, Price data, News | CNN + LSTM | RMSE, Profit | Keras, Python, TALIB |
| [178] | Stock of Tsugami Corporation | 2013 | Price data | LSTM | RMSE | Keras, Tensorflow |
| [179] | News, Nikkei Stock Average and 10-Nikkei companies | 1999–2008 | news, MACD | RNN, RBM+DBN | Accuracy, *P*-value | – |
| [180] | ISMIS 2017 Data Mining Competition dataset | – | Expert identifier, classes | LSTM + GRU + FFNN | Accuracy | – |
| [181] | Reuters, Bloomberg News, S&P500 price | 2006–2013 | News and sentences | LSTM | Accuracy | – |
| [182] | APPL from S&P500 and news from Reuters | 2011–2017 | Input news, OCHLV, Technical indicators | CNN + LSTM, CNN+SVM | Accuracy, F1-score | Tensorflow |
| [183] | Nikkei225, S&P500, news from Reuters and Bloomberg | 2001–2013 | Stock price data and news | DGM | Accuracy, MCC, %profit | – |
| [184] | Stocks from S&P500 | 2006–2013 | Text (news) and Price data | LAR+News, RF+News | MAPE, RMSE | – |

Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

# Deep learning for financial applications:

## Financial sentiment studies coupled with text mining without forecasting

| Art. | Data set | Period | Feature set | Method | Performance criteria | Env. |
|---|---|---|---|---|---|---|
| [85] | 883 BHC from EDGAR | 2006–2017 | Tokens, weighted sentiment polarity, leverage and ROA | CNN, LSTM, SVM, Random Forest | Accuracy, Precision, Recall, F1-score | Keras, Python, Scikit-learn |
| [185] | SemEval-2017 dataset, financial text, news, stock market data | 2017 | Sentiments in Tweets, News headlines | Ensemble SVR, CNN, LSTM, GRU | Cosine similarity score, agreement score, class score | Python, Keras, Scikit Learn |
| [186] | Financial news from Reuters | 2006–2015 | Word vector, Lexical and Contextual input | Targeted dependency tree LSTM | Cumulative abnormal return | – |
| [187] | Stock sentiment analysis from StockTwits | 2015 | StockTwits messages | LSTM, Doc2Vec, CNN | Accuracy, precision, recall, f-measure, AUC | – |
| [188] | Sina Weibo, Stock market records | 2012–2015 | Technical indicators, sentences | DRSE | F1-score, precision, recall, accuracy, AUROC | Python |
| [189] | News from NowNews, AppleDaily, LTN, MoneyDJ for 18 stocks | 2013–2014 | Text, Sentiment | LSTM, CNN | Return | Python, Tensorflow |
| [190] | StockTwits | 2008–2016 | Sentences, StockTwits messages | CNN, LSTM, GRU | MCC, WSURT | Keras, Tensorflow |
| [191] | Financial statements of Japan companies | – | Sentences, text | DMLP | Precision, recall, f-score | – |
| [192] | Twitter posts, news headlines | – | Sentences, text | Deep-FASP | Accuracy, MSE, $R^2$ | – |
| [193] | Forums data | 2004–2013 | Sentences and keywords | Recursive neural tensor networks | Precision, recall, f-measure | – |
| [194] | News from Financial Times related US stocks | – | Sentiment of news headlines | SVR, Bidirectional LSTM | Cosine similarity | Python, Scikit Learn, Keras, Tensorflow |

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# Deep learning for financial applications:
# Other text mining studies

| Art. | Data set | Period | Feature set | Method | Performance criteria | **Env.** |
|---|---|---|---|---|---|---|
| [72] | News from NowNews, AppleDaily, LTN, MoneyDJ for 18 stocks | 2013–2014 | Text, Sentiment | DMLP | Return | Python, Tensorflow |
| [86] | The event data set for large European banks, news articles from Reuters | 2007–2014 | Word, sentence | DMLP +NLP preprocess | Relative usefulness, F1-score | – |
| [87] | Event dataset on European banks, news from Reuters | 2007–2014 | Text, sentence | Sentence vector + DFFN | Usefulness, F1-score, AUROC | – |
| [88] | News from Reuters, fundamental data | 2007–2014 | Financial ratios and news text | doc2vec + NN | Relative usefulness | Doc2vec |
| [121] | Real-world data for automobile insurance company labeled as fradulent | – | Car, insurance and accident related features | DMLP + LDA | TP, FP, Accuracy, Precision, F1-score | – |
| [123] | Financial transactions | – | Transaction data | LSTM | t-SNE | – |
| [195] | Taiwan's National Pension Insurance | 2008–2014 | Insured's id, area-code, gender, etc. | RNN | Accuracy, total error | Python |
| [196] | StockTwits | 2015–2016 | Sentences, StockTwits messages | Doc2vec, CNN | Accuracy, precision, recall, f-measure, AUC | Python, Tensorflow |

Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

# Deep learning for financial applications:
# Other theoretical or conceptual studies

| Art. | SubTopic | IsTimeSeries? | Data set | Period | Feature set | Method |
|---|---|---|---|---|---|---|
| [197] | Analysis of AE, SVD | Yes | Selected stocks from the IBB index and stock of Amgen Inc. | 2012–2014 | Price data | AE, SVD |
| [198] | Fraud Detection in Banking | No | Risk Management / Fraud Detection | – | – | DRL |

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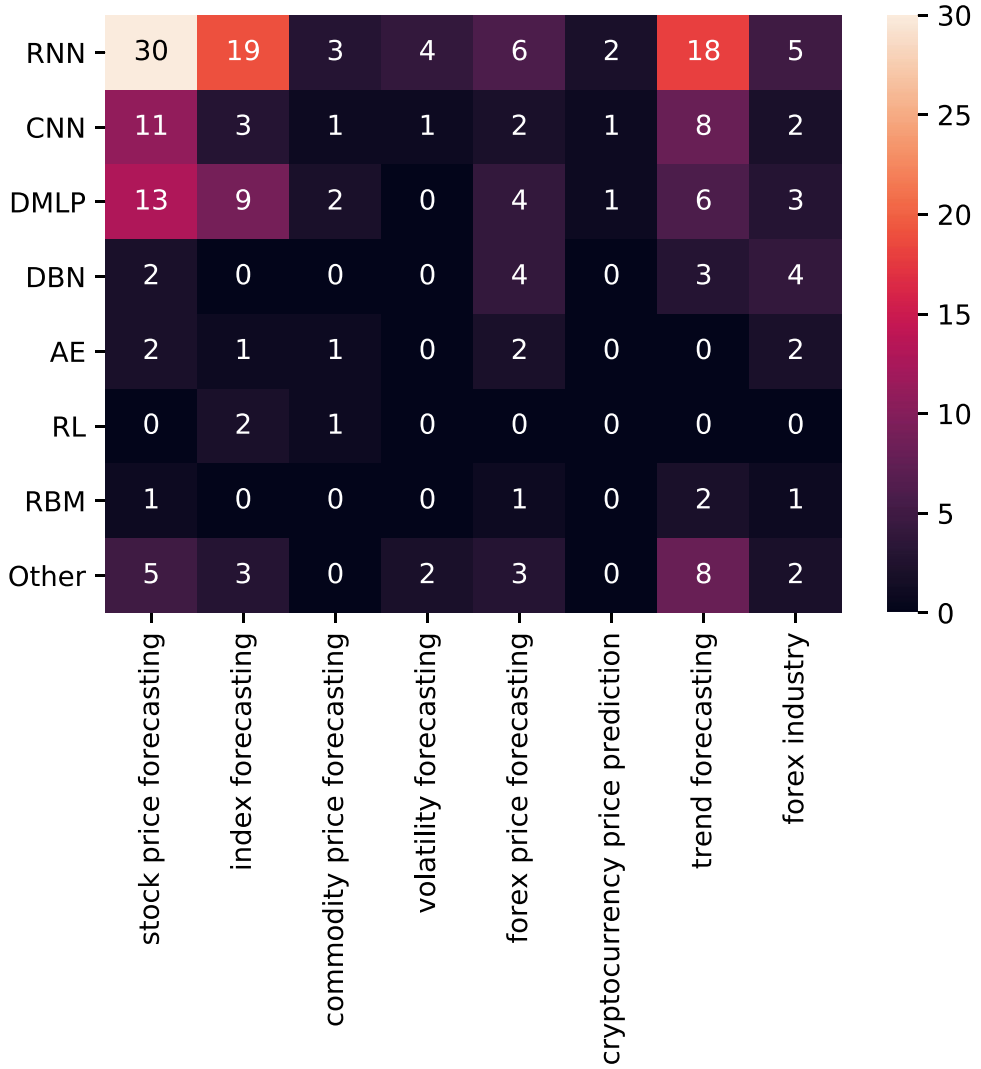
# Deep learning for financial applications:
# Other financial applications

| Art. | Subtopic | Data set | Period | Feature set | Method | Performance criteria | Env. |
|---|---|---|---|---|---|---|---|
| [47] | Improving trading decisions | S&P500, KOSPI, HSI, and EuroStoxx50 | 1987–2017 | 200-days stock price | Deep Q-Learning and DMLP | Total profit, Correlation | – |
| [193] | Identifying Top Sellers In Underground Economy | Forums data | 2004–2013 | Sentences and keywords | Recursive neural tensor networks | Precision, recall, f-measure | – |
| [195] | Predicting Social Ins. Payment Behavior | Taiwan's National Pension Insurance | 2008–2014 | Insured's id, area-code, gender, etc. | RNN | Accuracy, total error | Python |
| [199] | Speedup | 45 CME listed commodity and FX futures | 1991–2014 | Price data | DNN | – | – |
| [200] | Forecasting Fundamentals | Stocks in NYSE, NASDAQ or AMEX exchanges | 1970–2017 | 16 fundamental features from balance sheet | DMLP, LFM | MSE, Compound annual return, SR | – |
| [201] | Predicting Bank Telemarketing | Phone calls of bank marketing data | 2008–2010 | 16 finance-related attributes | CNN | Accuracy | – |
| [202] | Corporate Performance Prediction | 22 pharmaceutical companies data in US stock market | 2000–2015 | 11 financial and 4 patent indicator | RBM, DBN | RMSE, profit | – |

Source: Ahmet Murat Ozbayoglu, Mehmet Ugur Gudelek, and Omer Berat Sezer (2020). "Deep learning for financial applications: A survey." Applied Soft Computing (2020): 106384.

# Financial time series forecasting with deep learning: Topic-model heatmap




Source: Omer Berat Sezer, Mehmet Ugur Gudelek, and Ahmet Murat Ozbayoglu (2020), "Financial time series forecasting with deep learning: A systematic literature review: 2005–2019." Applied Soft Computing 90 (2020): 106181.

# Stock price forecasting using only raw time series data

| Art. | Data set | Period | Feature set | Lag | Horizon | Method | Performance criteria | Env. |
|---|---|---|---|---|---|---|---|---|
| [80] | 38 stocks in KOSPI | 2010–2014 | Lagged stock returns | 50 min | 5 min | DNN | NMSE, RMSE, MAE, MI | – |
| [81] | China stock market, 3049 Stocks | 1990–2015 | OCHLV | 30 d | 3 d | LSTM | Accuracy | Theano, Keras |
| [82] | Daily returns of 'BRD' stock in Romanian Market | 2001–2016 | OCHLV | – | 1 d | LSTM | RMSE, MAE | Python, Theano |
| [83] | 297 listed companies of CSE | 2012–2013 | OCHLV | 2 d | 1 d | LSTM, SRNN, GRU | MAD, MAPE | Keras |
| [84] | 5 stock in NSE | 1997–2016 | OCHLV, Price data, turnover and number of trades. | 200 d | 1..10 d | LSTM, RNN, CNN, MLP | MAPE | – |
| [85] | Stocks of Infosys, TCS and CIPLA from NSE | 2014 | Price data | – | – | RNN, LSTM and CNN | Accuracy | – |
| [86] | 10 stocks in S&P500 | 1997–2016 | OCHLV, Price data | 36 m | 1 m | RNN, LSTM, GRU | Accuracy, Monthly return | Keras, Tensorflow |
| [87] | Stocks data from S&P500 | 2011–2016 | OCHLV | 1 d | 1 d | DBN | MSE, norm-RMSE, MAE | – |
| [88] | High-frequency transaction data of the CSI300 futures | 2017 | Price data | – | 1 min | DNN, ELM, RBF | RMSE, MAPE, Accuracy | Matlab |
| [89] | Stocks in the S&P500 | 1990–2015 | Price data | 240 d | 1 d | DNN, GBT, RF | Mean return, MDD, Calmar ratio | H2O |
| [90] | ACI Worldwide, Staples, and Seagate in NASDAQ | 2006–2010 | Daily closing prices | 17 d | 1 d | RNN, ANN | RMSE | – |
| [91] | Chinese Stocks | 2007–2017 | OCHLV | 30 d | 1..5 d | CNN + LSTM | Annualized Return, Mxm Retracement | Python |
| [92] | 20 stocks in S&P500 | 2010–2015 | Price data | – | – | AE + LSTM | Weekly Returns | – |
| [93] | S&P500 | 1985–2006 | Monthly and daily log-returns | * | 1 d | DBN+MLP | Validation, Test Error | Theano, Python, Matlab |
| [94] | 12 stocks from SSE Composite Index | 2000–2017 | OCHLV | 60 d | 1..7 d | DWNN | MSE | Tensorflow |
| [95] | 50 stocks from NYSE | 2007–2016 | Price data | – | 1d, 3 d, 5 d | SFM | MSE | – |

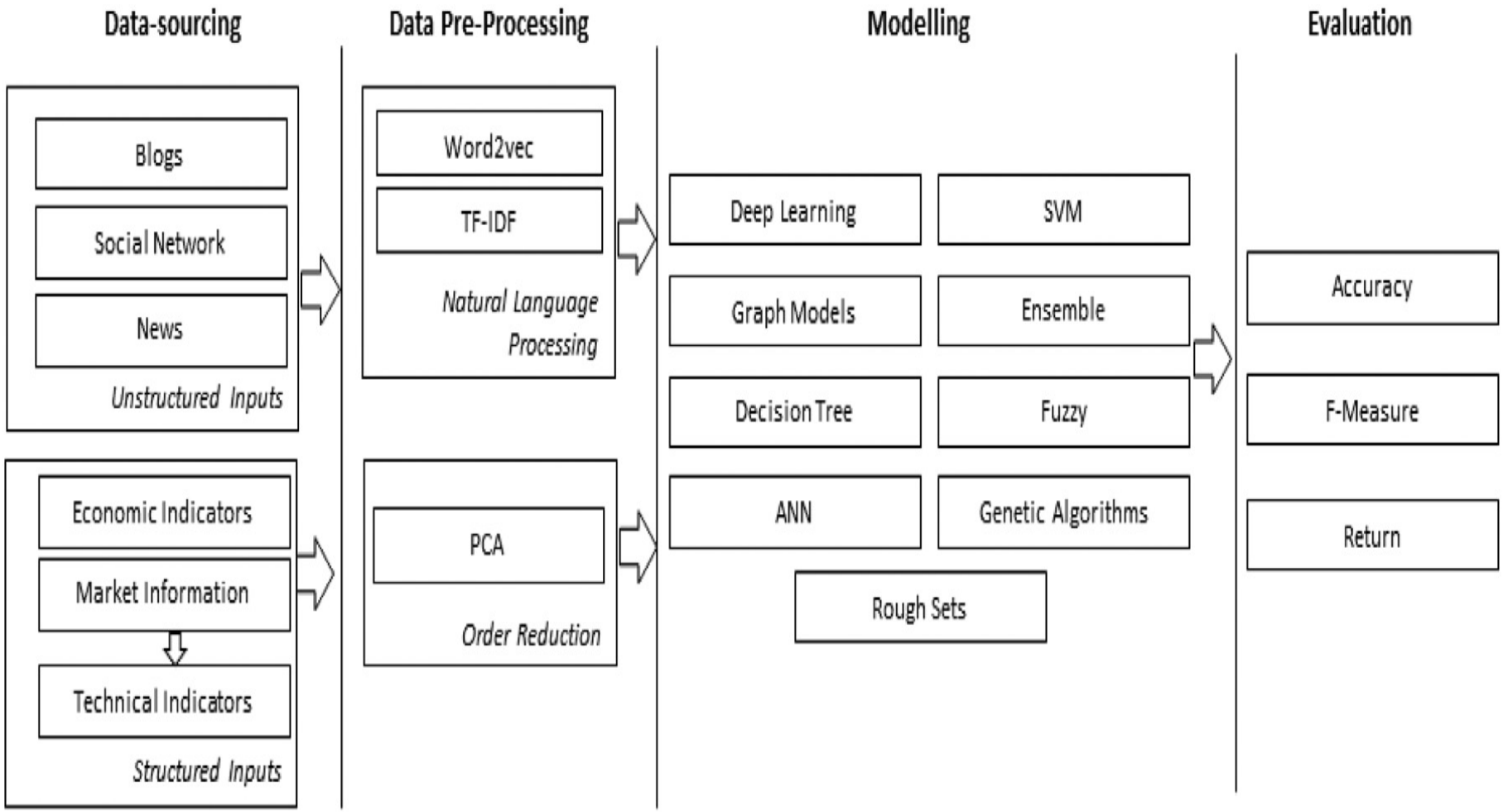
Source: Omer Berat Sezer, Mehmet Ugur Gudelek, and Ahmet Murat Ozbayoglu (2020), "Financial time series forecasting with deep learning: A systematic literature review: 2005–2019." Applied Soft Computing 90 (2020): 106181.

# Stock price forecasting using various data

| Art. | Data set | Period | Feature set | Lag | Horizon | Method | Performance criteria | Env. |
|---|---|---|---|---|---|---|---|---|
| [96] | Japan Index constituents from WorldScope | 1990–2016 | 25 Fundamental Features | 10 d | 1 d | DNN | Correlation, Accuracy, MSE | Tensorflow |
| [97] | Return of S&P500 | 1926–2016 | Fundamental Features: | – | 1 s | DNN | MSPE | Tensorflow |
| [98] | U.S. low-level disaggregated macroeconomic time series | 1959–2008 | GDP, Unemployment rate, Inventories, etc. | – | – | DNN | $R^2$ | – |
| [99] | CDAX stock market data | 2010–2013 | Financial news, stock market data | 20 d | 1 d | LSTM | MSE, RMSE, MAE, Accuracy, AUC | TensorFlow, Theano, Python, Scikit-Learn |
| [100] | Stock of Tsugami Corporation | 2013 | Price data | – | – | LSTM | RMSE | Keras, Tensorflow |
| [101] | Stocks in China's A-share | 2006–2007 | 11 technical indicators | – | 1 d | LSTM | AR, IR, IC | – |
| [102] | SCI prices | 2008–2015 | OCHL of change rate, price | 7 d | – | EmotionalAnalysis + LSTM | MSE | – |
| [103] | 10 stocks in Nikkei 225 and news | 2001–2008 | Textual information and Stock prices | 10 d | – | Paragraph Vector + LSTM | Profit | – |
| [104] | TKC stock in NYSE and QQQQ ETF | 1999–2006 | Technical indicators, Price | 50 d | 1 d | RNN (Jordan–Elman) | Profit, MSE | Java |
| [105] | 10 Stocks in NYSE | – | Price data, Technical indicators | 20 min | 1 min | LSTM, MLP | RMSE | – |
| [106] | 42 stocks in China's SSE | 2016 | OCHLV, Technical Indicators | 242 min | 1 min | GAN (LSTM, CNN) | RMSRE, DPA, GAN-F, GAN-D | – |
| [107] | Google's daily stock data | 2004–2015 | OCHLV, Technical indicators | 20 d | 1 d | $(2D)^2$ PCA + DNN | SMAPE, PCD, MAPE, RMSE, HR, TR, $R^2$ | R, Matlab |
| [108] | GarantiBank in BIST, Turkey | 2016 | OCHLV, Volatility, etc. | – | – | PLR, Graves LSTM | MSE, RMSE, MAE, RSE, $R^2$ | Spark |
| [109] | Stocks in NYSE, AMEX, NASDAQ, TAQ intraday trade | 1993–2017 | Price, 15 firm characteristics | 80 d | 1 d | LSTM+MLP | Monthly return, SR | Python,Keras, Tensorflow in AWS |
| [110] | Private brokerage company's real data of risky transactions | – | 250 features: order details, etc. | – | – | CNN, LSTM | F1-Score | Keras, Tensorflow |
| [111] | Fundamental and Technical Data, Economic Data | – | Fundamental , technical and market information | – | – | CNN | – | – |
| [112] | The LOB of 5 stocks of Finnish Stock Market | 2010 | FI-2010 dataset: bid/ask and volume | – | * | WMTR, MDA | Accuracy, Precision, Recall, F1-Score | – |
| [113] | Returns in NYSE, AMEX, NASDAQ | 1975–2017 | 57 firm characteristics | * | – | Fama–French n-factor model DL | $R^2$, RMSE | Tensorflow |

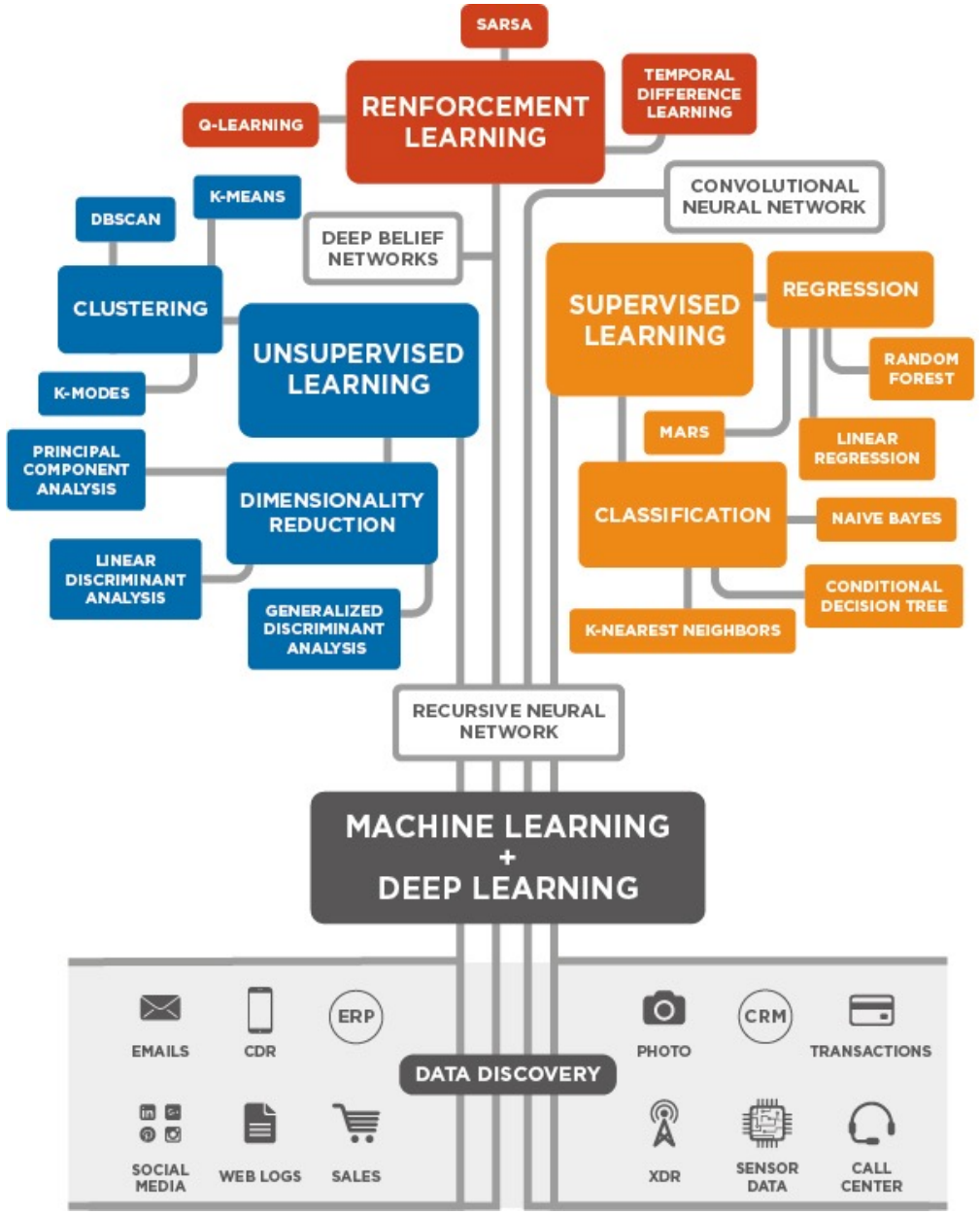
Source: Omer Berat Sezer, Mehmet Ugur Gudelek, and Ahmet Murat Ozbayoglu (2020), "Financial time series forecasting with deep learning: A systematic literature review: 2005–2019." Applied Soft Computing 90 (2020): 106181.

# Stock Market Movement Forecast:
# Phases of the stock market modeling



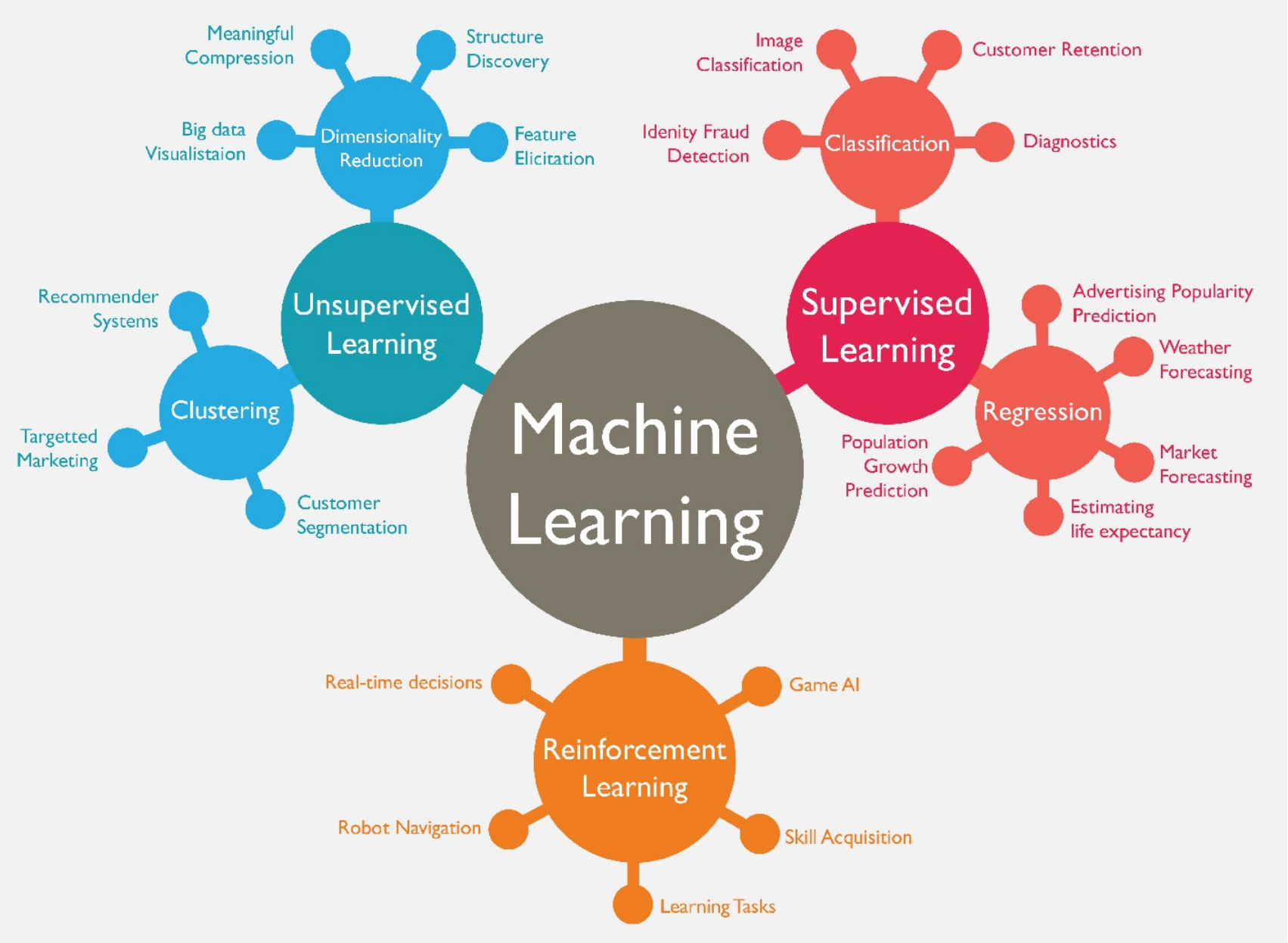

Source: O. Bustos and A. Pomares-Quimbaya (2020), "Stock Market Movement Forecast: A Systematic Review." Expert Systems with Applications (2020): 113464.

# 3 Machine Learning Algorithms




Source: Enrico Galimberti, http://blogs.teradata.com/data-points/tree-machine-learning-algorithms/

# Machine Learning (ML)



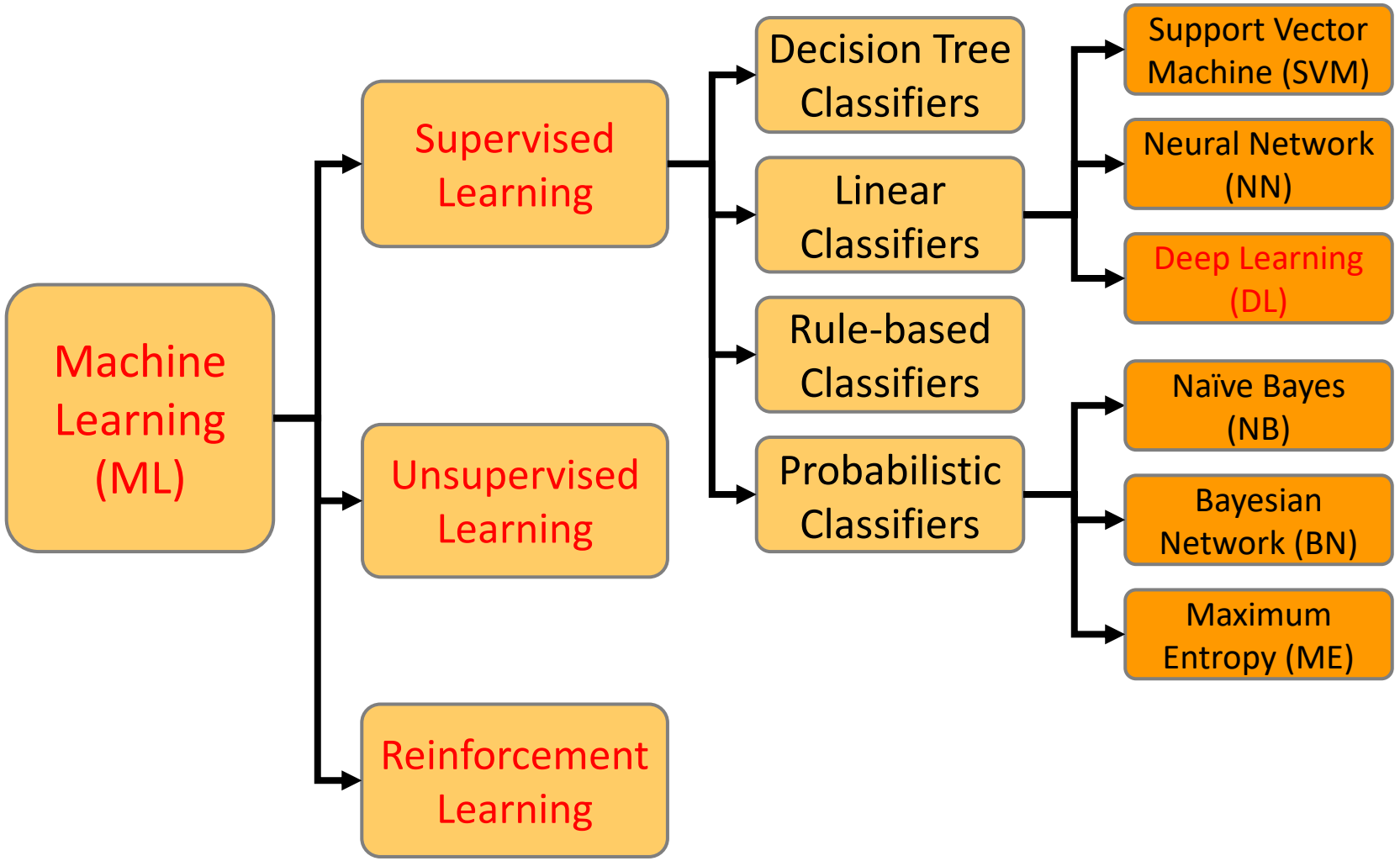

Source: https://www.mactores.com/services/aws-big-data-machine-learning-cognitive-services/

# Machine Learning Models

- Deep Learning
- Association rules
- Decision tree
- Clustering
- Bayesian
- Kernel
- Ensemble
- Dimensionality reduction
- Regression Analysis
- Instance based

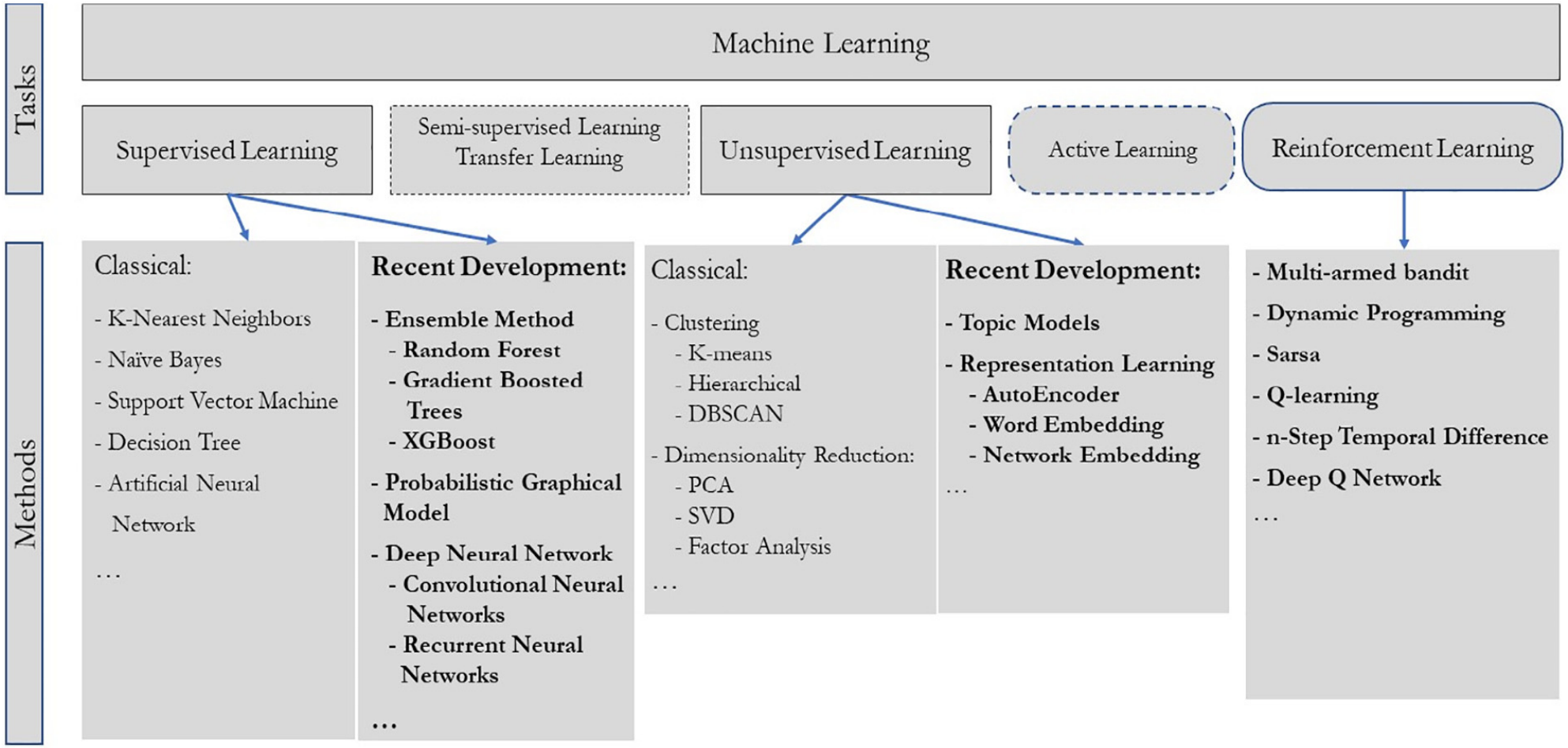
Source: Sunila Gollapudi (2016), Practical Machine Learning, Packt Publishing

# Machine Learning (ML) / Deep Learning (DL)




Source: Jesus Serrano-Guerrero, Jose A. Olivas, Francisco P. Romero, and Enrique Herrera-Viedma (2015), "Sentiment analysis: A review and comparative analysis of web services," Information Sciences, 311, pp. 18-38.

# Machine Learning Tasks and Methods




**Note:** Several entries in the diagram, e.g. word embedding or multi-armed bandit, refer to specific problem formulations for which a collection of methods exist.

: Tasks that take input data as given : Tasks that involve interactive data acquisition Dashed border: methods not elaborated in paper text

**Bold type**: highlights recent developments

Source: Liye Ma and Baohong Sun (2020), "Machine learning and AI in marketing – Connecting computing power to human insights." International Journal of Research in Marketing, 37, no. 3, 481-504.

# Decentralized Finance (DeFi)

# Block Chain FinTech

# Decentralized Finance (DeFi)

- A global, open alternative to the current financial system.
- Products that let you borrow, save, invest, trade, and more.
- Based on open-source technology that anyone can program with.

Source: https://ethereum.org/en/defi/

# Traditional Finance
# Centralized Finance (CeFi)

- Some people aren't granted access to set up a bank account or use financial services.
- Lack of access to financial services can prevent people from being employable.
- Financial services can block you from getting paid.
- A hidden charge of financial services is your personal data.
- Governments and centralized institutions can close down markets at will.
- Trading hours often limited to business hours of specific time zone.
- Money transfers can take days due to internal human processes.
- There's a premium to financial services because intermediary institutions need their cut.

Source: https://ethereum.org/en/defi/

# DeFi vs. CeFi

| Decentralized Finance (DeFi) | Traditional Finance (Centralized Finance; CeFi) |
|---|---|
| You hold your money. | Your money is held by companies. |
| You control where your money goes and how it's spent. | You have to trust companies not to mismanage your money, like lend to risky borrowers. |
| Transfers of funds happen in minutes. | Payments can take days due to manual processes. |
| Transaction activity is pseudonymous. | Financial activity is tightly coupled with your identity. |
| DeFi is open to anyone. | You must apply to use financial services. |
| The markets are always open. | Markets close because employees need breaks. |
| It's built on transparency – anyone can look at a product's data and inspect how the system works. | Financial institutions are closed books: you can't ask to see their loan history, a record of their managed assets, and so on. |

Source: https://ethereum.org/en/defi/

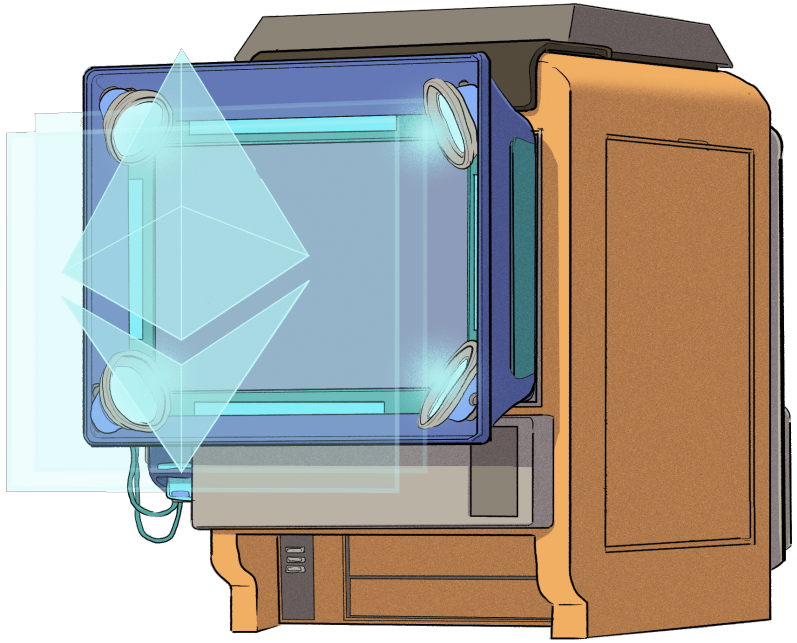
# (DeFi)
# Decentralized Applications (Dapps)

- **Ethereum-powered tools and services**
- **Dapps are a growing movement of applications that use Ethereum to disrupt business models or invent new ones**

Source: https://ethereum.org/en/defi/

# The Internet of Assets

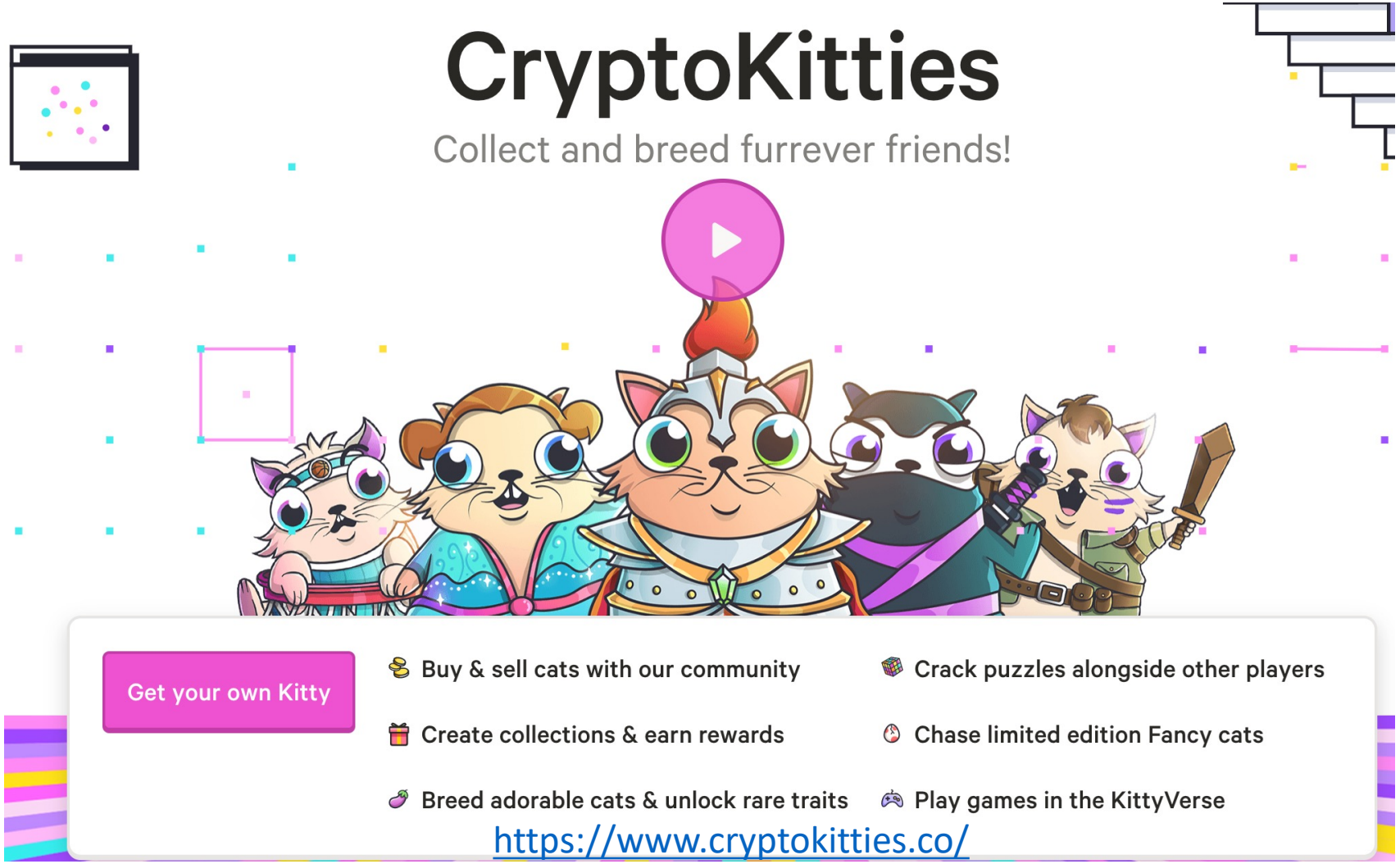
- **Ethereum** isn't just for **digital money**.
- Anything you can own can be **represented**, **traded** and **put to use** as **non-fungible tokens (NFTs)**.



Source: https://ethereum.org/en/defi/

# Non-Fungible Tokens (NFT)

## CryptoKitties




Source: Matt Fortnow and QuHarrison Terry (2021), The NFT Handbook - How to Create, Sell and Buy Non-Fungible Tokens, Wiley

# Top Stablecoins
# (Tether USDT, USD Coin USDC, Dai)

**Digital money for everyday use**

Stablecoins are
Ethereum tokens designed to
stay at a fixed value,
even when
the price of ETH changes.

| CURRENCY | MARKET CAPITALIZATION | COLLATERAL TYPE |
|---|---|---|
| Tether | $69,136,810,713 | Fiat |
| USD Coin | $32,359,142,012 | Fiat |
| Binance USD | $13,083,174,132 | Fiat |
| Dai | $6,265,852,093 | Crypto |
| TrueUSD | $1,347,100,594 | Fiat |
| PAX Gold | $318,953,291 | Precious metals |
| HUSD | $296,254,105 | Fiat |
| Gemini Dollar | $231,786,547 | Fiat |

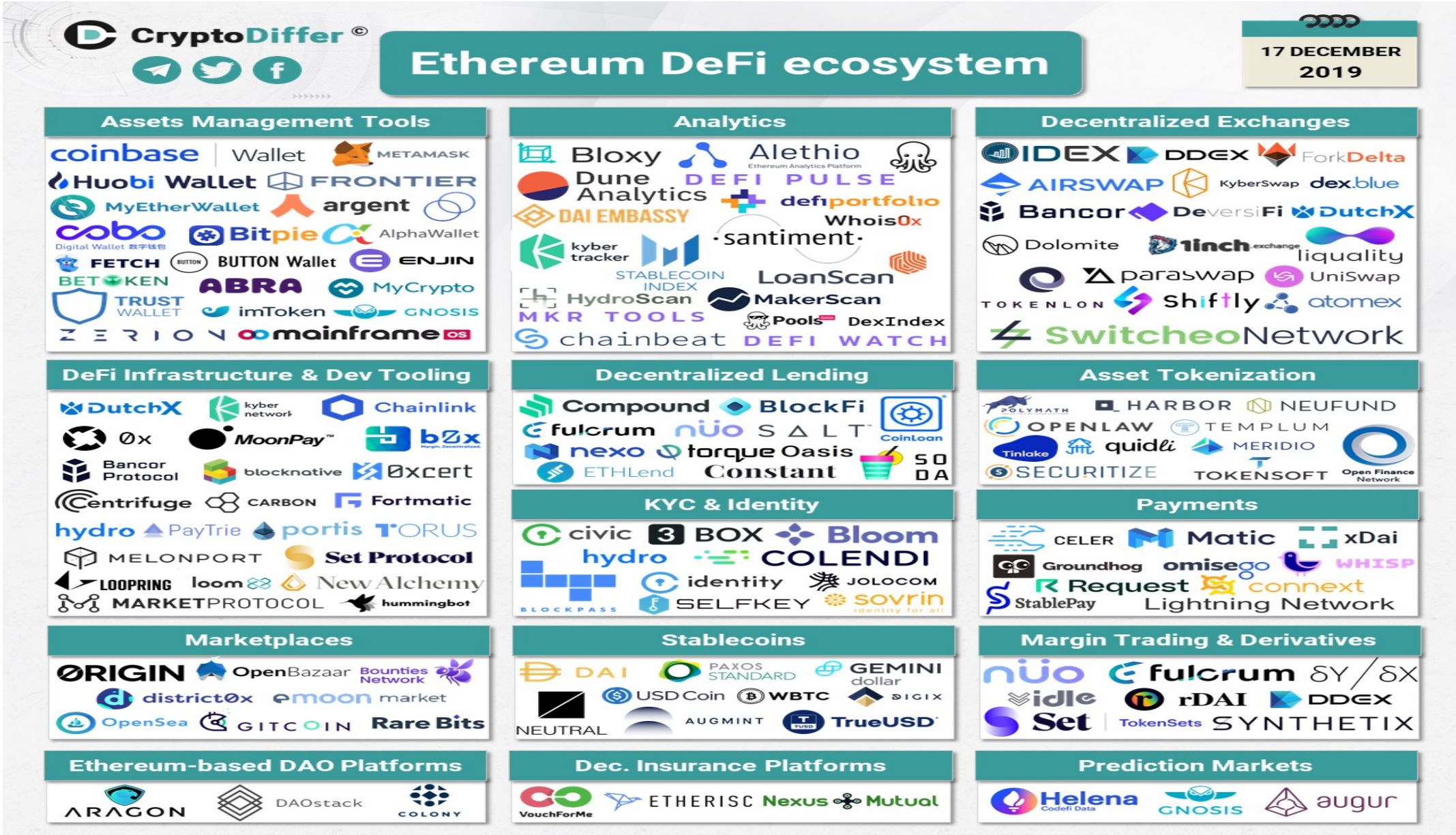
Source: https://ethereum.org/en/stablecoins/

# Financial Stability Challenges

| | |
|---|---|
| **Crypto Ecosystem** | • **Operational, cyber, and governance risks**<br>• **Integrity (market and AML/CFT)**<br>(Anti–Money Laundering / Combating the Financing of Terrorism)<br>• **Data availability / reliability**<br>• **Challenges from cross-boarder activites** |
| **Stablecoins** | • **How stable are stablecoins?**<br>• **Domestic and global regulatory and supervisory approaches** |
| **Macro-Financial** | • **Cryptoization, capital flows, and restrictions**<br>• **Monetary policy transmission**<br>• **Bank disintermediation** |

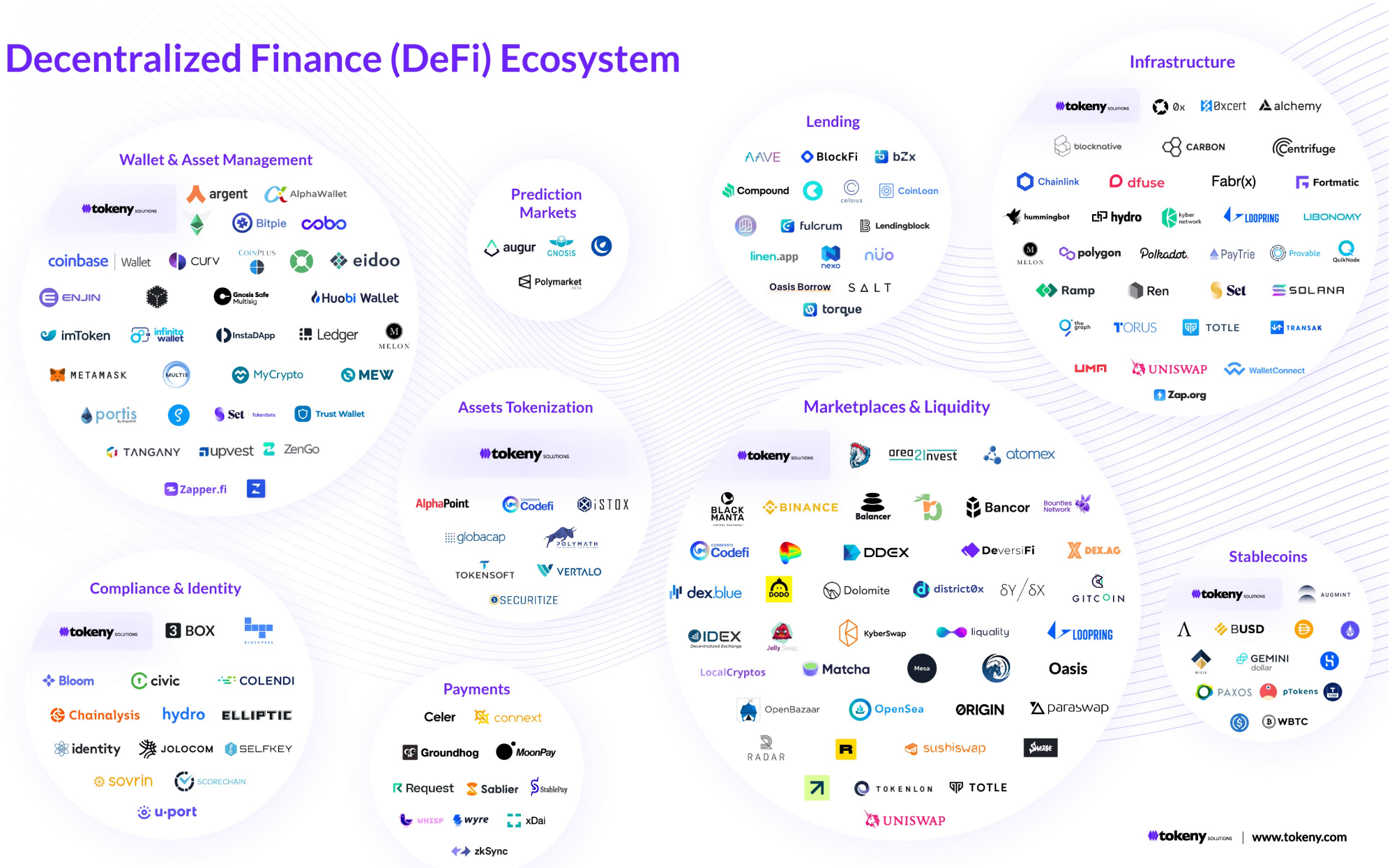
Source: Parma Bains, Mohamed Diaby, Dimitris Drakopoulos, Julia Faltermeier, Federico Grinberg, Evan Papageorgiou, Dmitri Petrov, Patrick Schneider, and Nobu Sugimoto (2021), The Crypto Ecosystem and Financial Stability Challenges, International Monetary Fund, October 2021

# Ethereum DeFi Ecosystem




Source: https://cryptodiffer.com/news/ethereum-defi-ecosystem/

# Decentralized Finance (DeFi) Ecosystem




Source: https://tokeny.com/defi-ecosystem/

# Outline

- **AI in FinTech: Financial Services Innovation and Application**
- **Artificial Intelligence for Knowledge Graphs of Cryptocurrency Anti-money Laundering in Fintech**

The 12th International Workshop on Mining and Analyzing Social Networks for Decision Support (MSNDS 2021)
ASONAM 2021, Virtual Event, Netherlands, November 8-11, 2021

# Artificial Intelligence for Knowledge Graphs of Cryptocurrency Anti-money Laundering in Fintech

Time: November 8, 2021, 14:00 – 15:40 [Amsterdam Time GMT+2] MSNDS 2021 (Room:Tehran)

**Min-Yuh Day, Ph.D,**
**Associate Professor**

**Graduate Institute of Information Management,**
**National Taipei University, Taiwan**

https://web.ntpu.edu.tw/~myday

# Knowledge Graph (KG)

- **Knowledge Graph (KG)**
  - **A knowledge graph is a multi-relational graph composed of entities and relations, which are regarded as nodes and different types of edges, respectively (Ji et al., 2021).**
  - **Represents knowledge as concepts (entities) and their relationships (Facts)**
  - **Triple of facts**
    - *SPO: (subject, predicate, object)*
    - *HRT: (head, relation, tail)*
- **Common Knowledge Graph: DBpedia, YAGO, Wikidata**

# Knowledge Graph, Facts, Triple, Embedding

- $G$
  - Knowledge graph
- $F$
  - Set of facts
- $(h, r, t)$
  - Triple of head, relation, and tail
- **(h, r, t)**
  - Embedding of head, relation, and tail

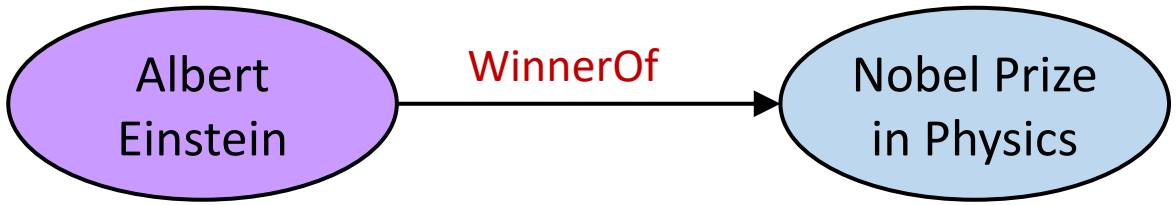
Source: Ji, S., Pan, S., Cambria, E., Marttinen, P., & Philip, S. Y. (2021). A survey on knowledge graphs: Representation, acquisition, and applications. IEEE Transactions on Neural Networks and Learning Systems.

# Knowledge Representation
# Factual Triple and Knowledge Graph

- Albert Einstein, winner of the 1921 Nobel prize in physics
- The Nobel Prize in Physics 1921 was awarded to Albert Einstein "for his services to Theoretical Physics, and especially for his discovery of the law of the photoelectric effect."

**Triple** (Albert Einstein, **WinnerOf**, Nobel Prize in Physics)

**Knowledge Graph**



# Factual Triples in Knowledge Base

*(h, r, t)*

(Albert Einstein, **BornIn**, German Empire)

(Albert Einstein, **SonOf**, Hermann Einstein)

(Albert Einstein, **GraduateFrom**, University of Zurich)

(Albert Einstein, **WinnerOf**, Nobel Prize in Physics)

(Albert Einstein, **ExpertIn**, Physics)

(Nobel Prize in Physics, **AwardIn**, Physics)

(The theory of relativity, **TheoryOf**, Physics)

(Albert Einstein, **SupervisedBy**, Alfred Kleiner)

(Alfred Kleiner, **ProfessorOf**, University of Zurich)

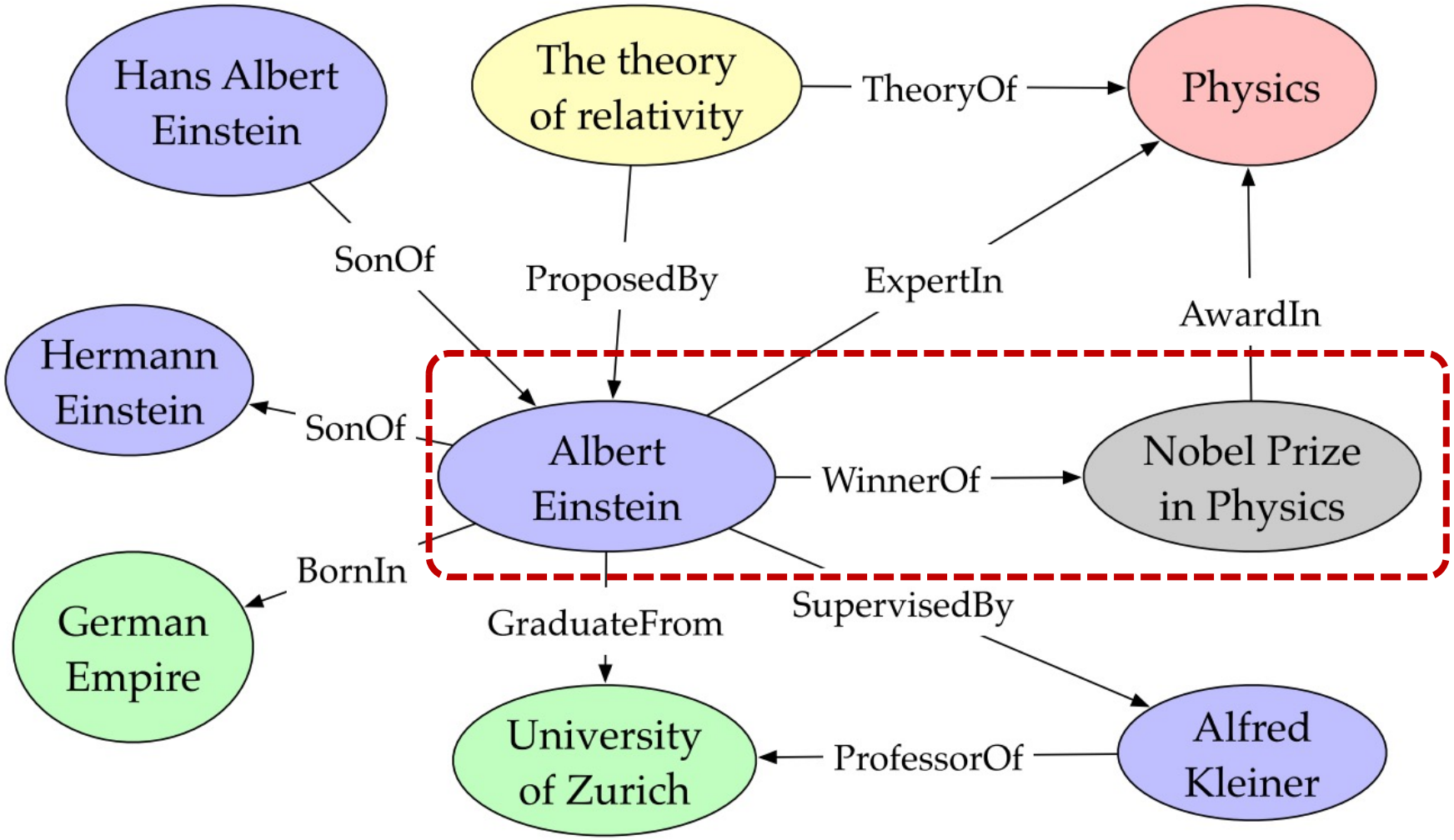
(The theory of relativity, **ProposedBy**, Albert Einstein)

(Hans Albert Einstein, **SonOf**, Albert Einstein)

Source: Ji, S., Pan, S., Cambria, E., Marttinen, P., & Philip, S. Y. (2021). A survey on knowledge graphs: Representation, acquisition, and applications. IEEE Transactions on Neural Networks and Learning Systems.

# Entities and Relations in Knowledge Graph

(Albert Einstein, **WinnerOf**, Nobel Prize in Physics)



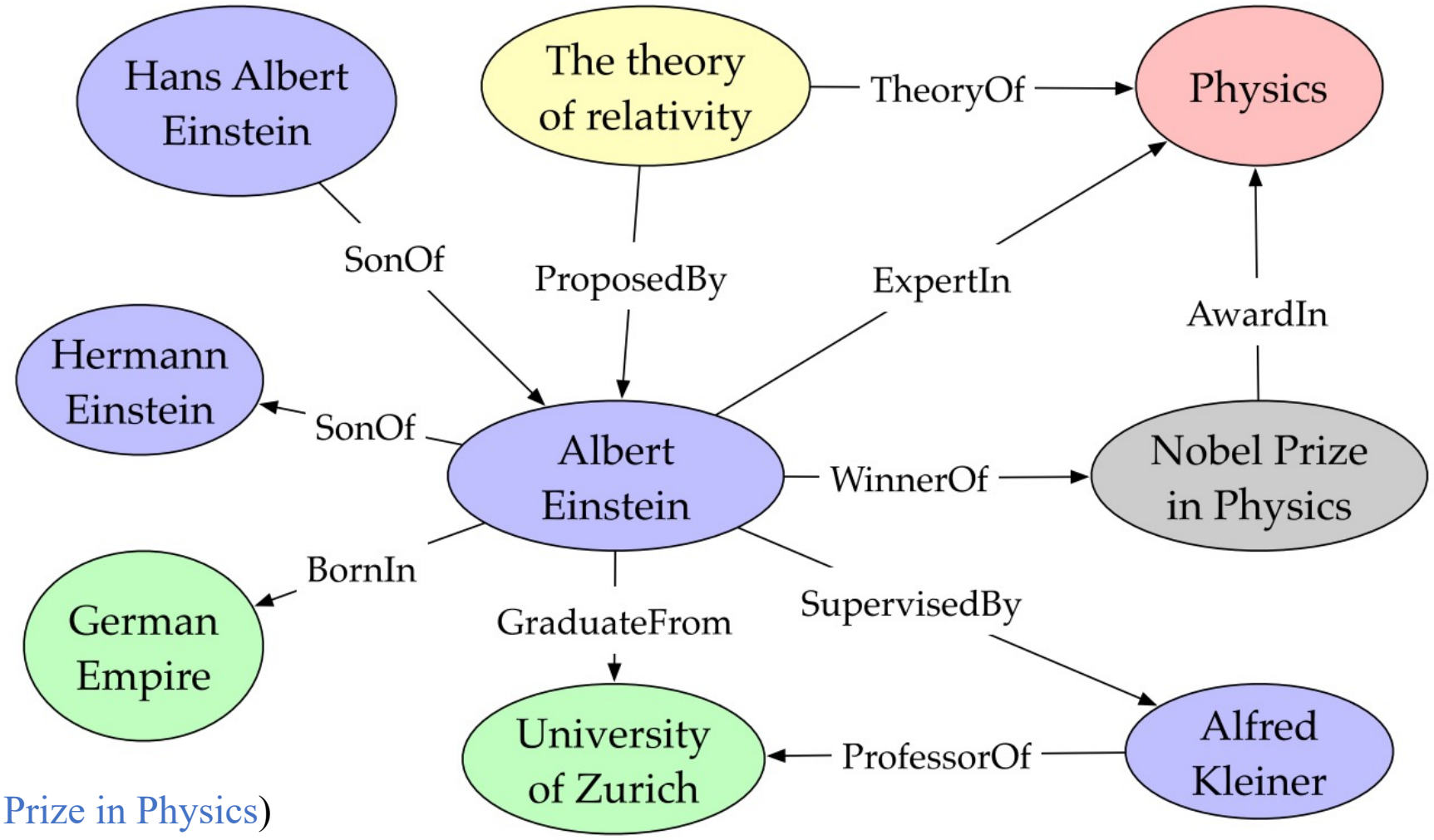

Source: Ji, S., Pan, S., Cambria, E., Marttinen, P., & Philip, S. Y. (2021). A survey on knowledge graphs: Representation, acquisition, and applications. IEEE Transactions on Neural Networks and Learning Systems.

# knowledge base and knowledge graph

## Factual triples in knowledge base

(Albert Einstein, **BornIn**, German Empire)
(Albert Einstein, **SonOf**, Hermann Einstein)
(Albert Einstein, **GraduateFrom**, University of Zurich)
(Albert Einstein, **WinnerOf**, Nobel Prize in Physics)
(Albert Einstein, **ExpertIn**, Physics)
(Nobel Prize in Physics, **AwardIn**, Physics)
(The theory of relativity, **TheoryOf**, Physics)
(Albert Einstein, **SupervisedBy**, Alfred Kleiner)
(Alfred Kleiner, **ProfessorOf**, University of Zurich)
(The theory of relativity, **ProposedBy**, Albert Einstein)
(Hans Albert Einstein, **SonOf**, Albert Einstein)

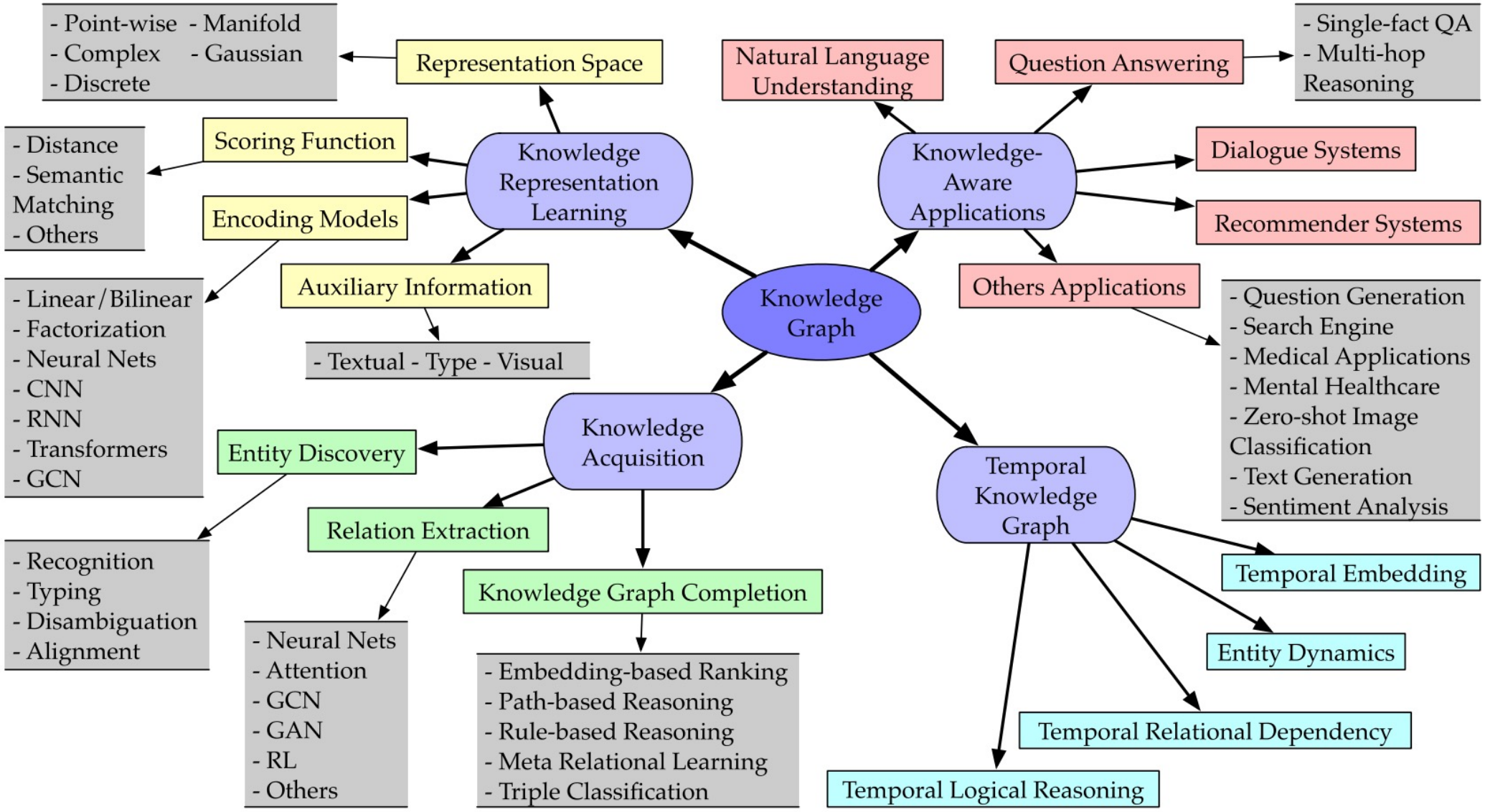
## Entities and relations in knowledge graph




(Albert Einstein, **WinnerOf**, Nobel Prize in Physics)

Source: Ji, S., Pan, S., Cambria, E., Marttinen, P., & Philip, S. Y. (2021). A survey on knowledge graphs: Representation, acquisition, and applications. IEEE Transactions on Neural Networks and Learning Systems.

# Categorization of Research on Knowledge Graphs




Source: Ji, S., Pan, S., Cambria, E., Marttinen, P., & Philip, S. Y. (2021). A survey on knowledge graphs: Representation, acquisition, and applications. IEEE Transactions on Neural Networks and Learning Systems.

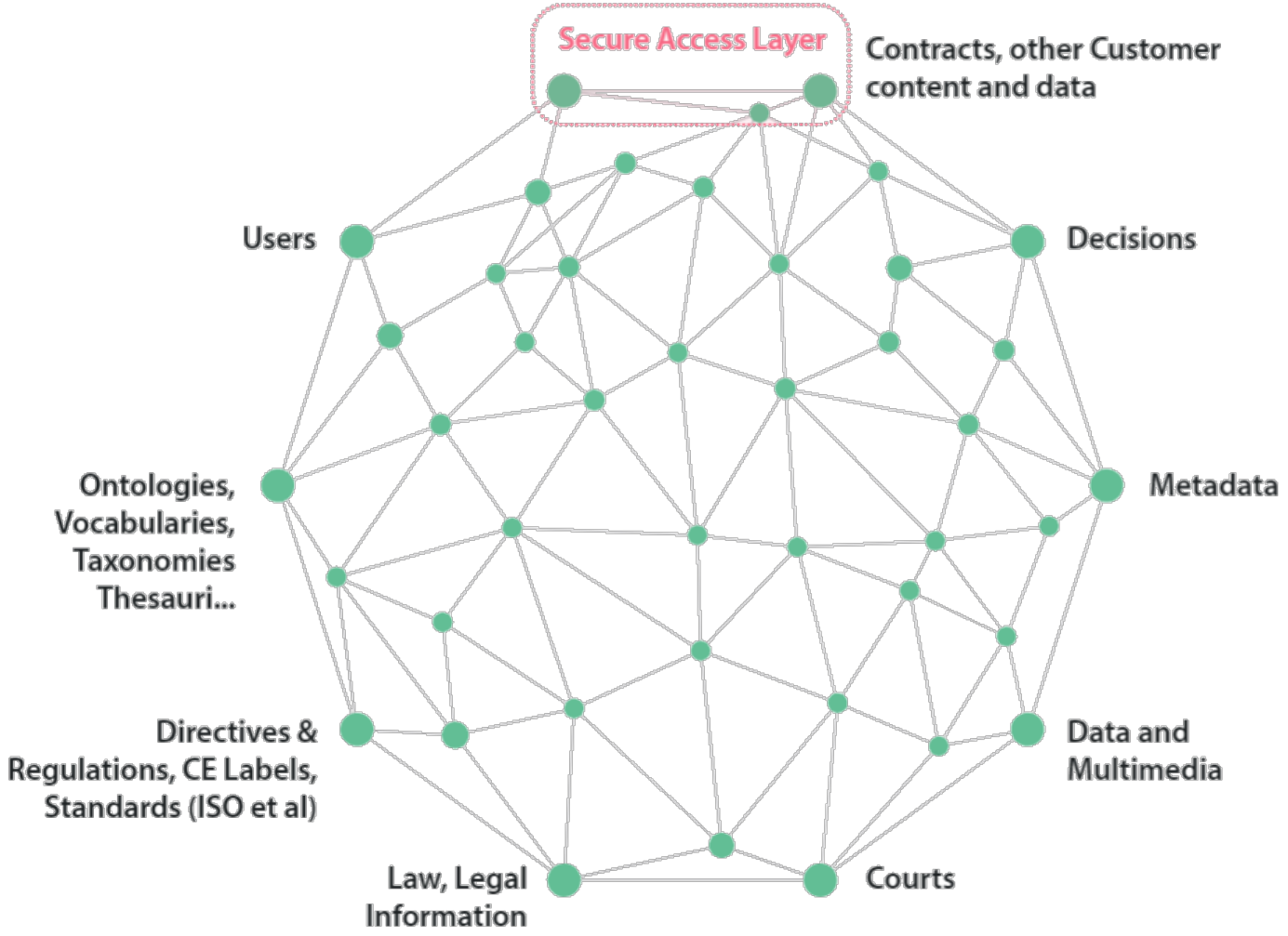
# Knowledge Graph Completion (KGC) Datasets

| Knowledge Graph Completion (KGC) Dataset | #Entity | #Relation | #Train | #Valid | #Test | Reference |
|---|---|---|---|---|---|---|
| **WN18RR** | 40,943 | 11 | 86,835 | 3,034 | 3,134 | Toutanova & Chen (2015); Zhang et al. (2020) |
| **FB15k-237** | 14,541 | 237 | 272,115 | 17,535 | 20,466 | Dettmers et al. (2018); Zhang et al. (2020) |
| **YAGO3-10** | 123,182 | 37 | 1,079,040 | 5,000 | 5,000 | Mahdisoltani et al. (2015); Zhang et al. (2020) |

# Domain-Specific Knowledge Graph

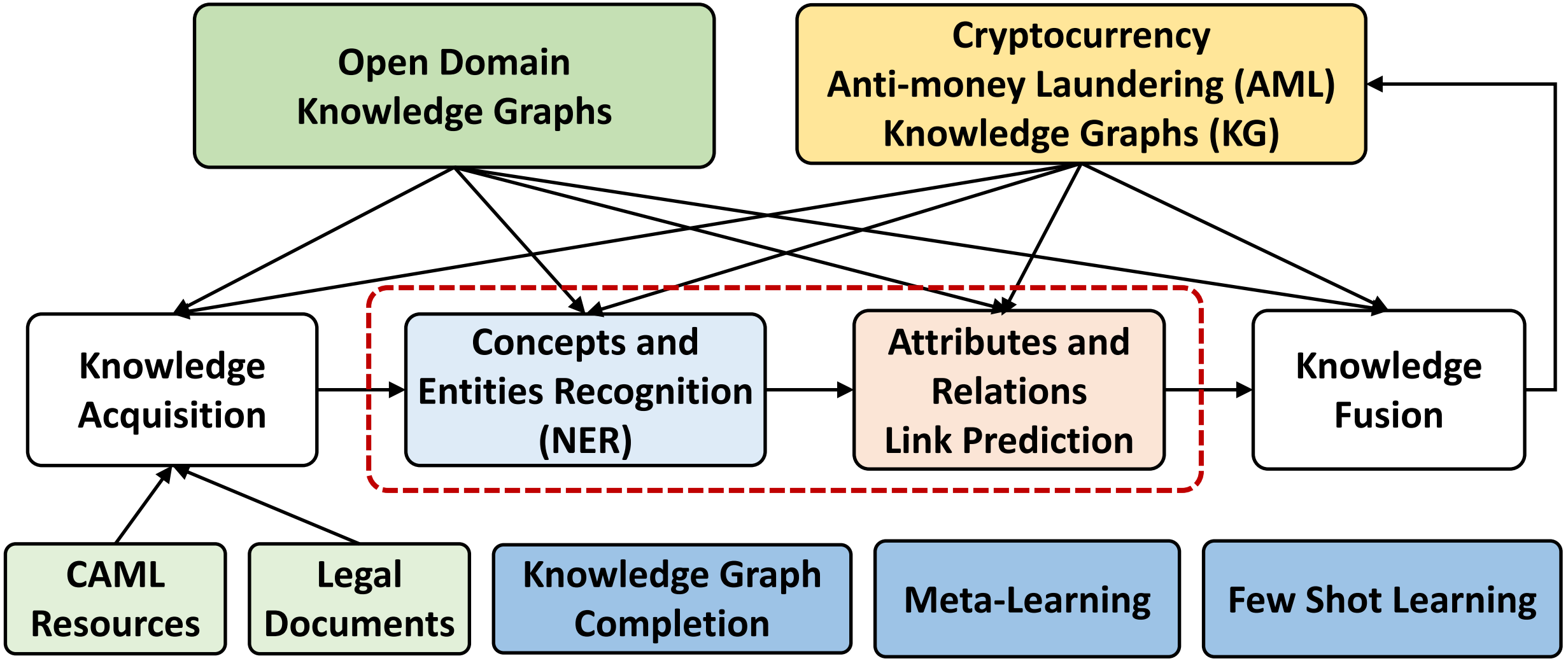
- **Domain-Specific Knowledge Graph**
  - **PubMed Knowledge Graph (PKG)**
    - **Extracting biological entities from 29 million PubMed abstracts**
  - **Lynx: Legal Knowledge Graph for Multilingual Compliance Services**
    - Legal Knowledge Graph (LKG) integrates and links heterogeneous compliance data sources including legislation, case law, standards and other private contracts.

# Lynx: Legal Knowledge Graph for Multilingual Compliance Services



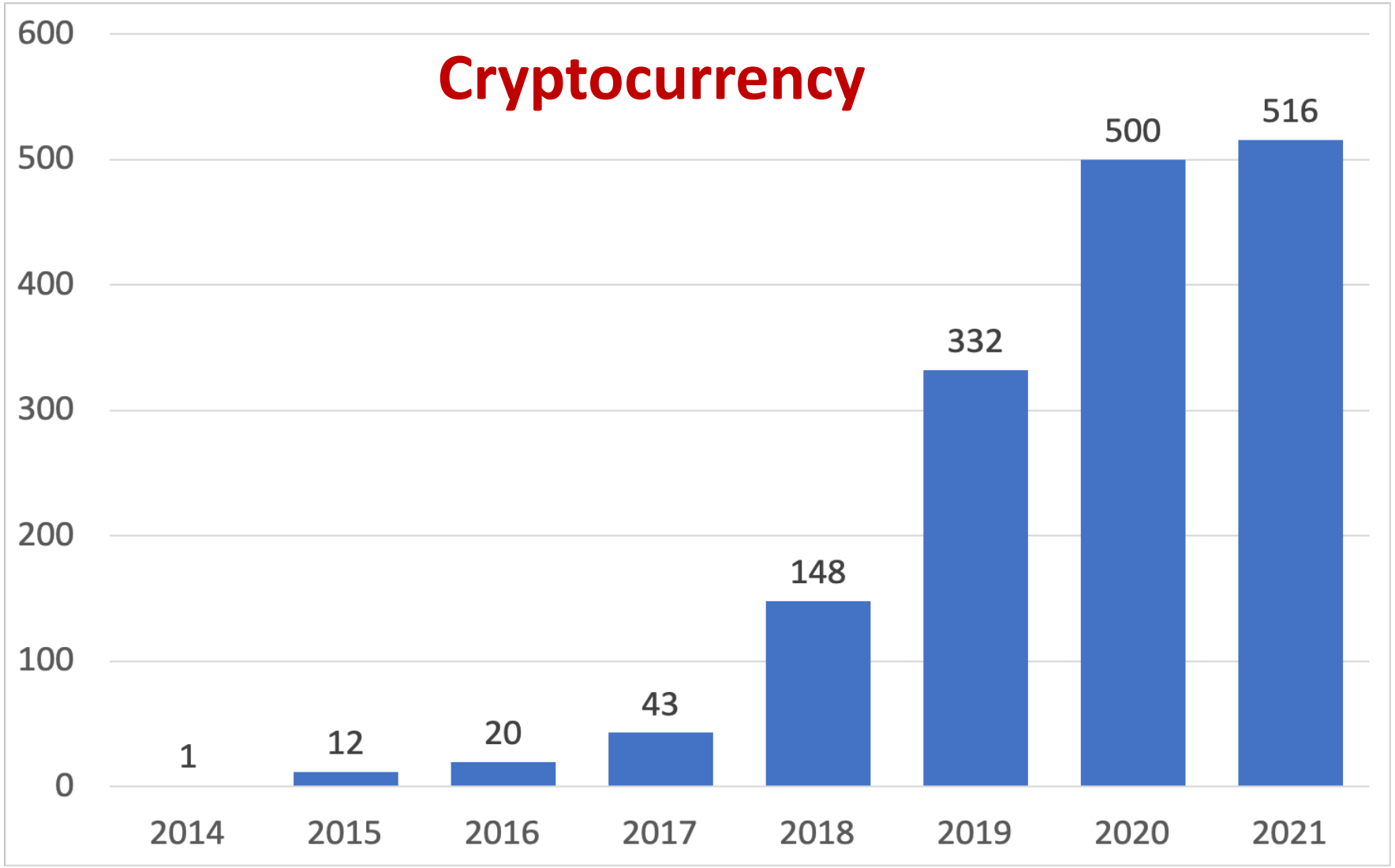

Source: Lynx Legal Knowledge Graph (LKG), https://lynx-project.eu/

# System Architecture for Cryptocurrency Anti-money Laundering (AML) Knowledge Graphs




Source: Min-Yuh Day (2021), "Artificial Intelligence for Knowledge Graphs of Cryptocurrency Anti-money Laundering in Fintech",
in Proceedings of the 2021 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM 2021), Virtual Event, Netherlands, November 8-11, 2021.

# Research Trend of Cryptocurrency Research on Web of Science (2014-2021)

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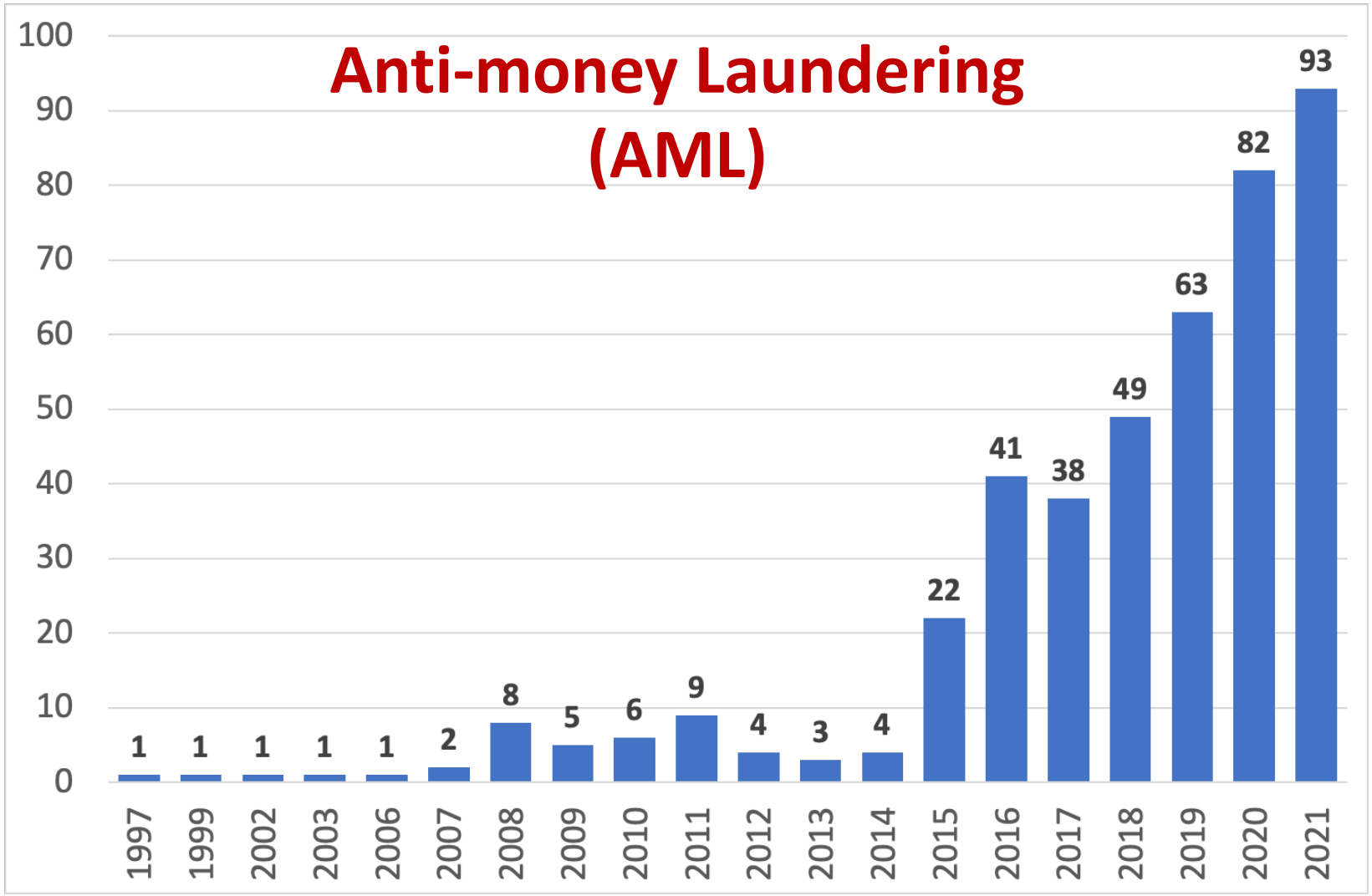
# Research Trend of Anti-money Laundering Research on Web of Science (1997-2021)




Source: Min-Yuh Day (2021), "Artificial Intelligence for Knowledge Graphs of Cryptocurrency Anti-money Laundering in Fintech", in Proceedings of the 2021 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM 2021), Virtual Event, Netherlands, November 8-11, 2021.

# Top keywords in Cryptocurrency

| Rank | Keyword | Frequency | Percentage |
|---|---|---|---|
| 1 | bitcoin | 945 | 6.91% |
| 2 | cryptocurrency | 825 | 6.03% |
| 3 | blockchain | 523 | 3.82% |
| 4 | cryptocurrencies | 247 | 1.81% |
| 5 | volatility | 222 | 1.62% |
| 6 | inefficiency | 148 | 1.08% |
| 7 | gold | 128 | 0.94% |
| 8 | hedge | 88 | 0.64% |
| 9 | ethereum | 85 | 0.62% |
| 10 | economics | 75 | 0.55% |
| 11 | returns | 73 | 0.53% |
| 12 | security | 63 | 0.46% |
| 13 | technology | 59 | 0.43% |
| 14 | internet | 56 | 0.41% |
| 15 | market | 56 | 0.41% |
| 16 | risk | 55 | 0.40% |
| 17 | safe haven | 54 | 0.39% |
| 18 | smart contracts | 53 | 0.39% |
| 19 | garch | 51 | 0.37% |
| 20 | model | 51 | 0.37% |

Source: Min-Yuh Day (2021), "Artificial Intelligence for Knowledge Graphs of Cryptocurrency Anti-money Laundering in Fintech",
in Proceedings of the 2021 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM 2021), Virtual Event, Netherlands, November 8-11, 2021.

# Word Cloud for Cryptocurrency


Source: Min-Yuh Day (2021), "Artificial Intelligence for Knowledge Graphs of Cryptocurrency Anti-money Laundering in Fintech",
in Proceedings of the 2021 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM 2021), Virtual Event, Netherlands, November 8-11, 2021.

# Top keywords in Anti-money Laundering

| Rank | Keyword | Frequency | Percentage |
|---|---|---|---|
| 1 | money laundering | 173 | 7.15% |
| 2 | anti-money laundering | 91 | 3.76% |
| 3 | compliance | 31 | 1.28% |
| 4 | aml | 26 | 1.07% |
| 5 | corruption | 23 | 0.95% |
| 6 | crime | 20 | 0.83% |
| 7 | fatf | 20 | 0.83% |
| 8 | terrorism | 17 | 0.70% |
| 9 | risk | 15 | 0.62% |
| 10 | governance | 14 | 0.58% |
| 11 | regulation | 13 | 0.54% |
| 12 | anti-money laundering (aml) | 12 | 0.50% |
| 13 | blockchain | 12 | 0.50% |
| 14 | financial action task force | 12 | 0.50% |
| 15 | lawyers | 12 | 0.50% |
| 16 | terrorism financing | 12 | 0.50% |
| 17 | bitcoin | 11 | 0.45% |
| 18 | customer due diligence | 11 | 0.45% |
| 19 | financial crime | 11 | 0.45% |
| 20 | global governance | 11 | 0.45% |

Source: Min-Yuh Day (2021), "Artificial Intelligence for Knowledge Graphs of Cryptocurrency Anti-money Laundering in Fintech",
in Proceedings of the 2021 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM 2021), Virtual Event, Netherlands, November 8-11, 2021.

# Word Cloud for Anti-money Laundering


Source: Min-Yuh Day (2021), "Artificial Intelligence for Knowledge Graphs of Cryptocurrency Anti-money Laundering in Fintech",
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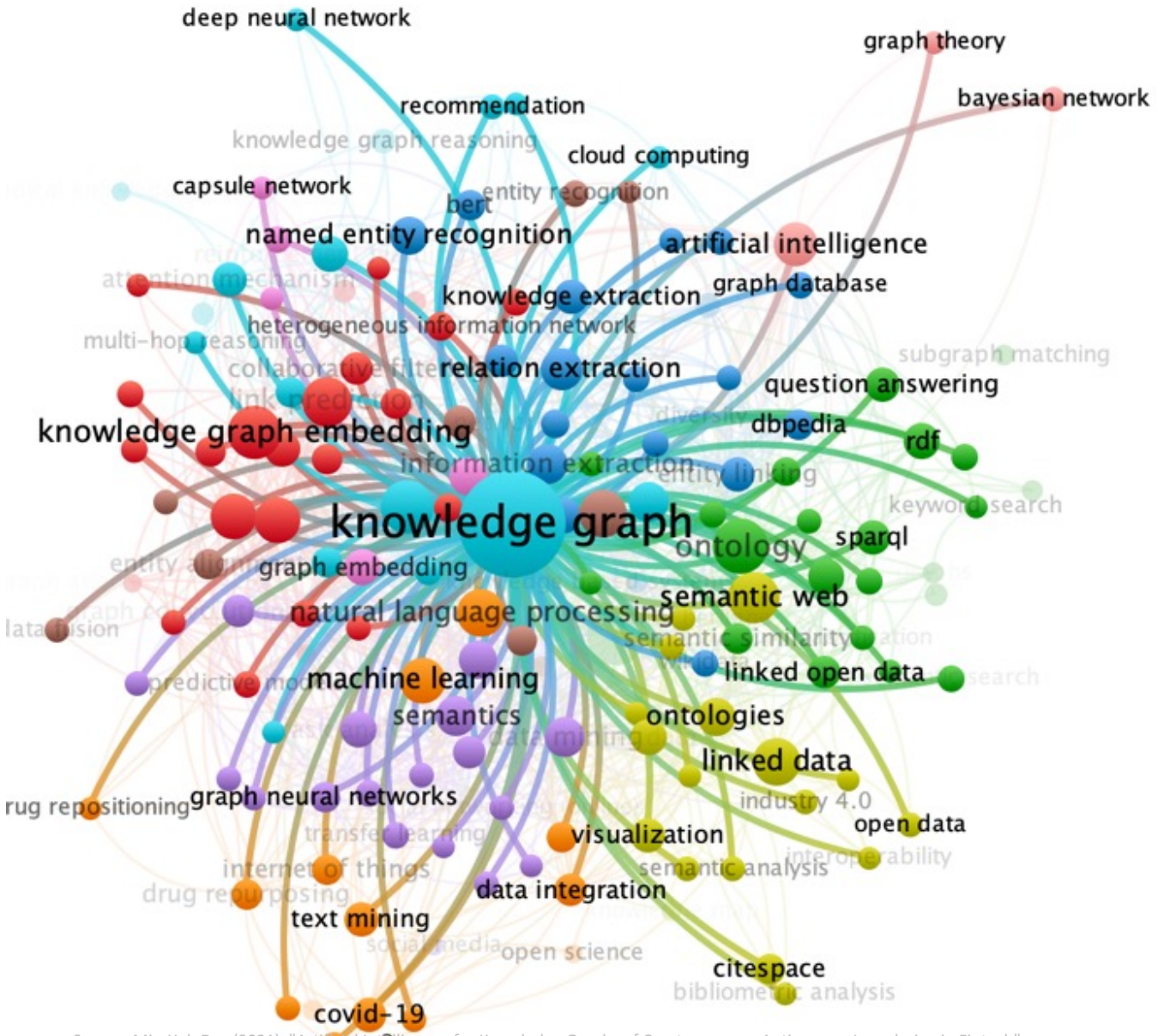
# Keyword Co-occurrence of Knowledge Graph

**VOSviewer:**
**Visualizing scientific landscapes**

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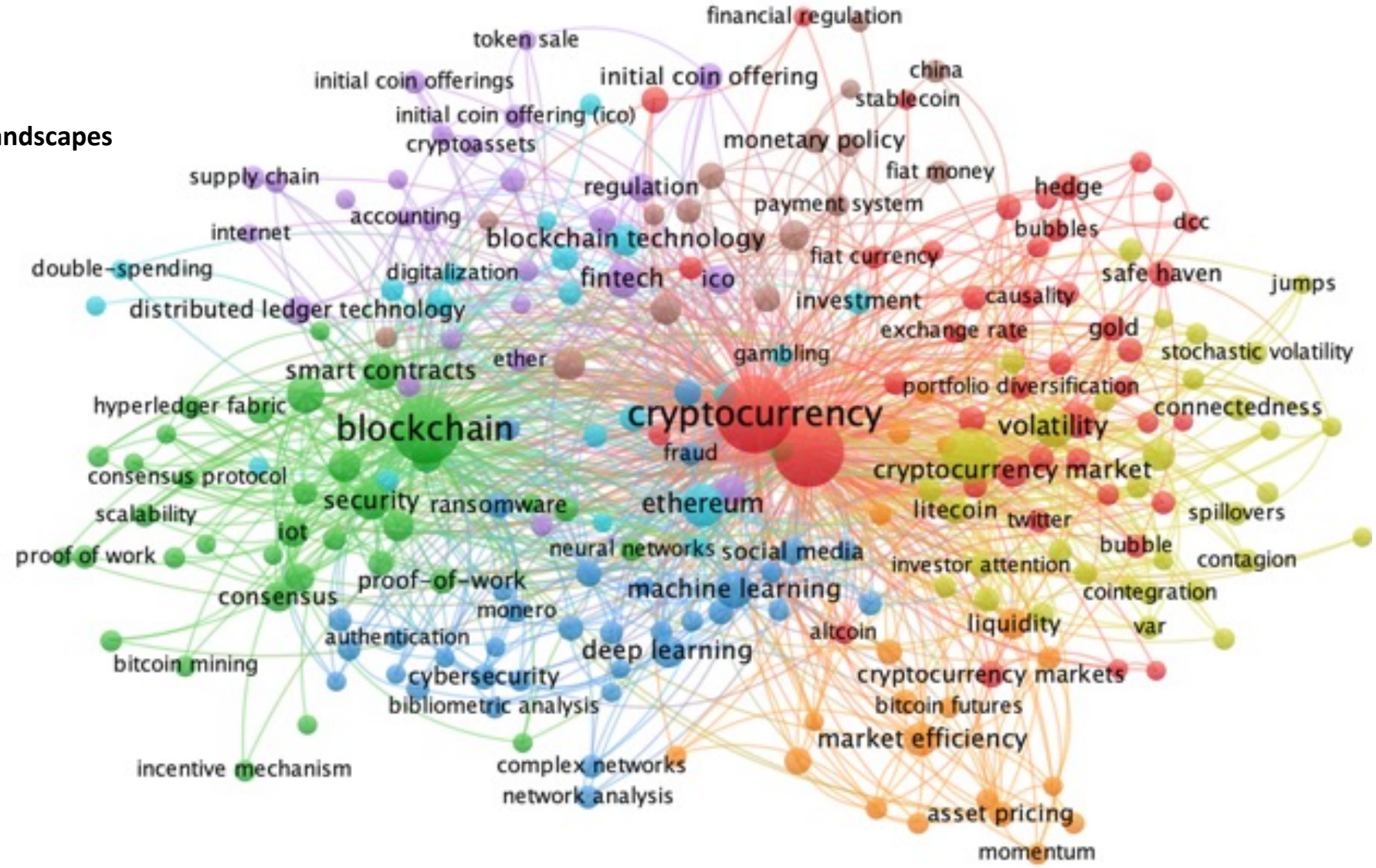
# Cryptocurrency

**VOSviewer:**
**Visualizing scientific landscapes**

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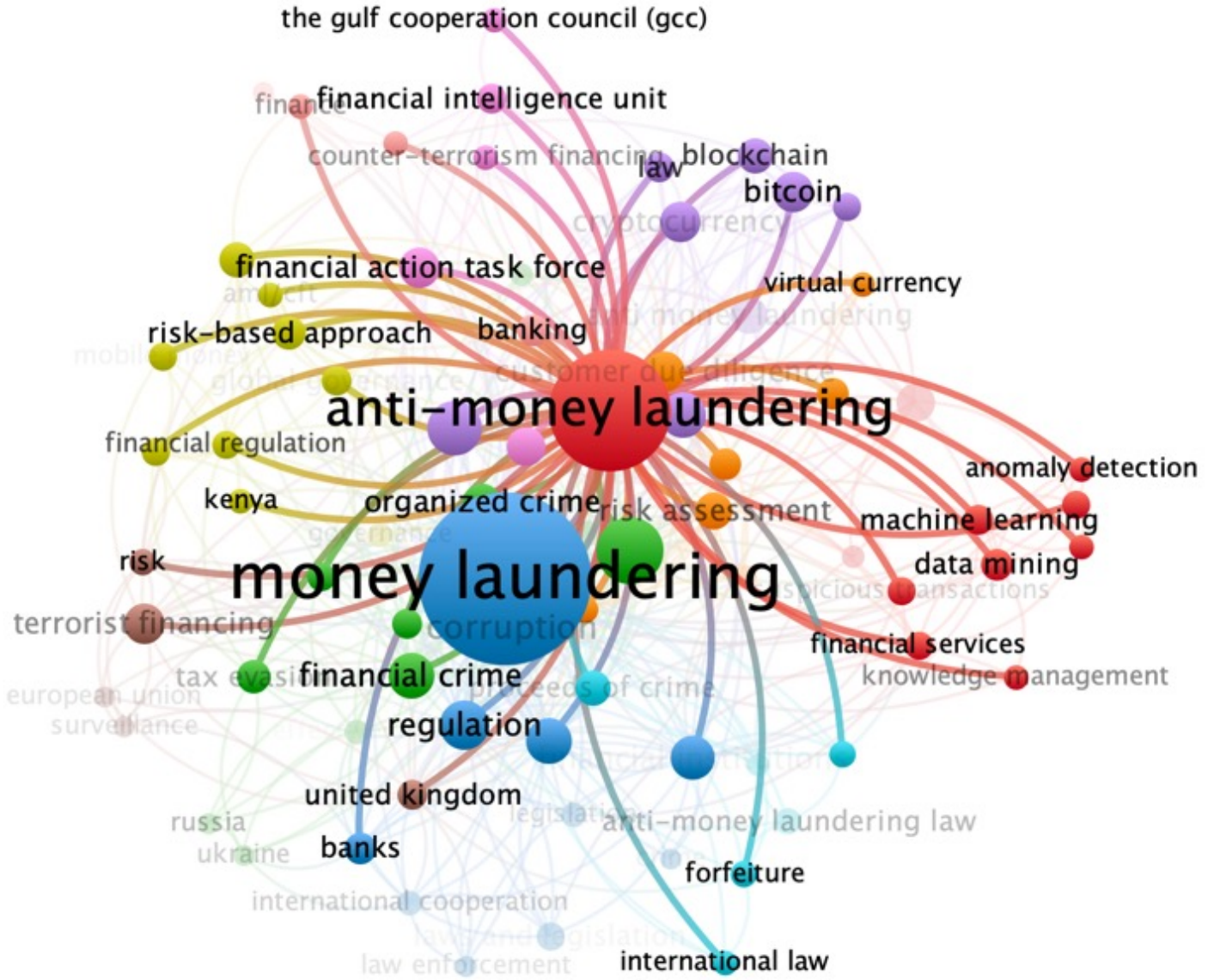
# Anti-money Laundering

**VOSviewer:**
**Visualizing scientific landscapes**

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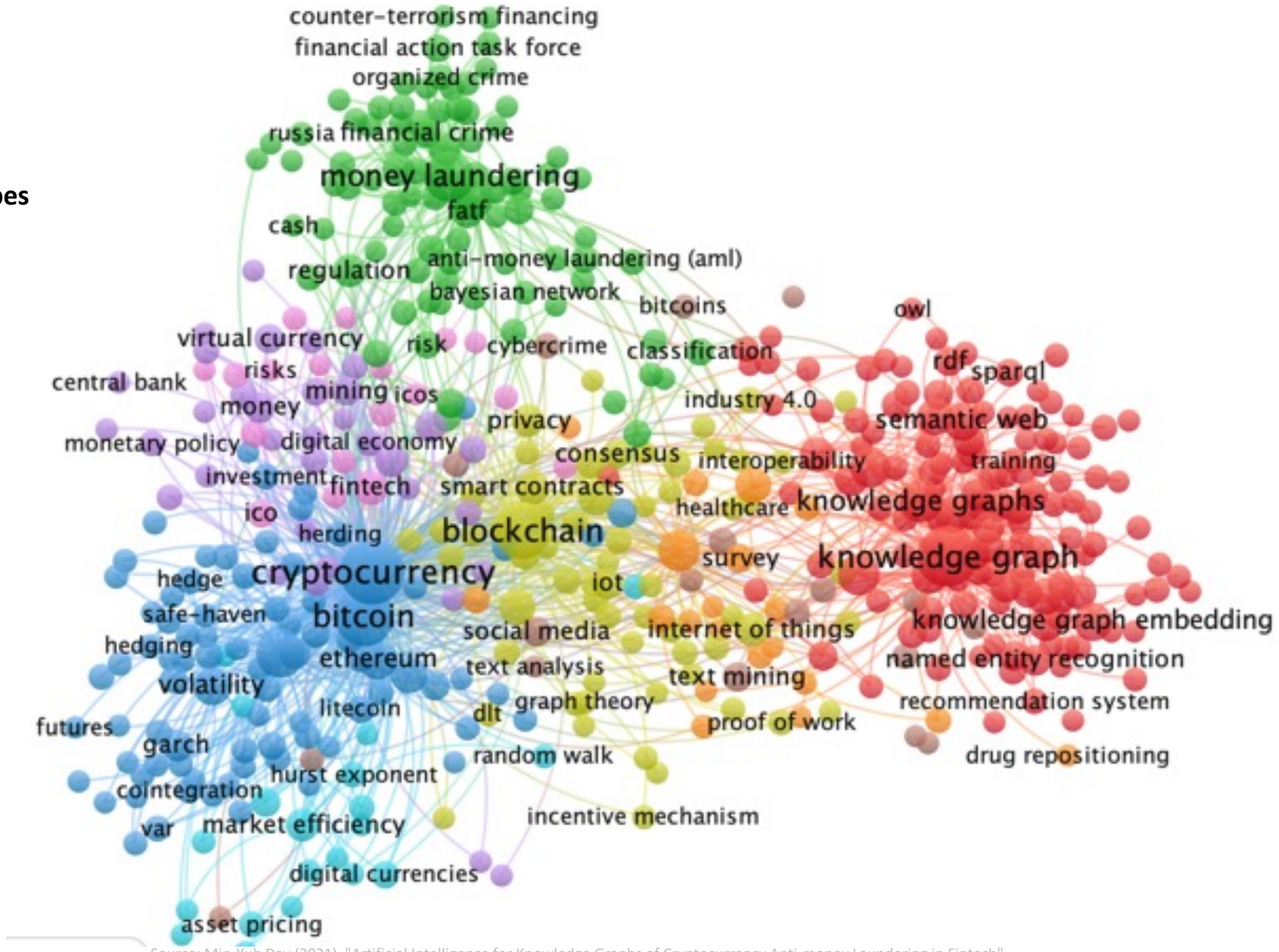
in Proceedings of the 2021 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM 2021), Virtual Event, Netherlands, November 8-11, 2021.

# Knowledge Graphs, Cryptocurrency, Anti-money Laundering

**VOSviewer:**
**Visualizing scientific landscapes**

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# Top 20 Journal Published Cryptocurrency Research on Web of Science (Total Journals: 1572)

| Rank | Journal | Count | Percentage |
|---|---|---|---|
| 1 | Finance Research Letters | 82 | 5.22% |
| 2 | IEEE Access | 61 | 3.88% |
| 3 | Journal of Risk and Financial Management | 40 | 2.54% |
| 4 | Physica a-Statistical Mechanics and Its Applications | 39 | 2.48% |
| 5 | Economics Letters | 33 | 2.10% |
| 6 | Research in International Business and Finance | 29 | 1.84% |
| 7 | International Review of Financial Analysis | 28 | 1.78% |
| 8 | Mathematics | 21 | 1.34% |
| 9 | Applied Economics Letters | 20 | 1.27% |
| 10 | Applied Economics | 17 | 1.08% |
| 11 | Journal of Alternative Investments | 16 | 1.02% |
| 12 | Frontiers in Blockchain | 14 | 0.89% |
| 13 | Sustainability | 13 | 0.83% |
| 14 | North American Journal of Economics and Finance | 12 | 0.76% |
| 15 | Plos One | 12 | 0.76% |
| 16 | Future Generation Computer Systems-the International Journal of Escience | 11 | 0.70% |
| 17 | Journal of International Financial Markets Institutions & Money | 11 | 0.70% |
| 18 | Journal of Money Laundering Control | 11 | 0.70% |
| 19 | Technological Forecasting and Social Change | 10 | 0.64% |
| 20 | Chaos Solitons & Fractals | 9 | 0.57% |

Source: Min-Yuh Day (2021), "Artificial Intelligence for Knowledge Graphs of Cryptocurrency Anti-money Laundering in Fintech",
in Proceedings of the 2021 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM 2021), Virtual Event, Netherlands, November 8-11, 2021.

# Top 20 Journal Published Anti-money Laundering research on Web of Science (Total Journals: 160)

| Rank | Journal | Count | Percentage |
|---|---|---|---|
| 1 | Journal of Money Laundering Control | 197 | 45.39% |
| 2 | Crime Law and Social Change | 18 | 4.15% |
| 3 | Trusts & Trustees | 9 | 2.07% |
| 4 | Journal of Financial Regulation and Compliance | 8 | 1.84% |
| 5 | European Journal on Criminal Policy and Research | 6 | 1.38% |
| 6 | Financial and Credit Activity-Problems of Theory and Practice | 6 | 1.38% |
| 7 | IEEE Access | 4 | 0.92% |
| 8 | Journal of Banking Regulation | 4 | 0.92% |
| 9 | International Journal of Disclosure and Governance | 3 | 0.69% |
| 10 | International Review of Law and Economics | 3 | 0.69% |
| 11 | Journal of Criminal Law | 3 | 0.69% |
| 12 | Security Dialogue | 3 | 0.69% |
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# Summary

- **AI in FinTech: Financial Services Innovation and Application**
- **Artificial Intelligence for Knowledge Graphs of Cryptocurrency Anti-money Laundering in Fintech**

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Computer Science and Information Engineering, National Taiwan University of Science and Technology

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