Machine Learning

3 key questions

What is Machine Learning?

In [ ]:

```
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Why is Machine Learning relevant for Banking?

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In [ ]:
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What are the Main Challenges of Machine Learning?

In [ ]:

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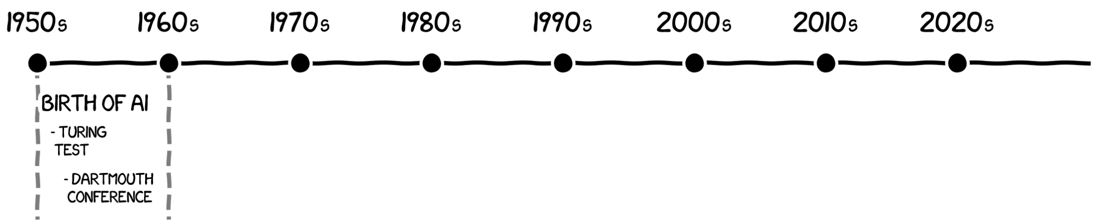
Map

1. Introduction to AI
2. Economics of Machine Learning
3. AI & Finance
4. Challenges
5. Policy & Regulation

1. Introduction to AI

1.1. AI as a research field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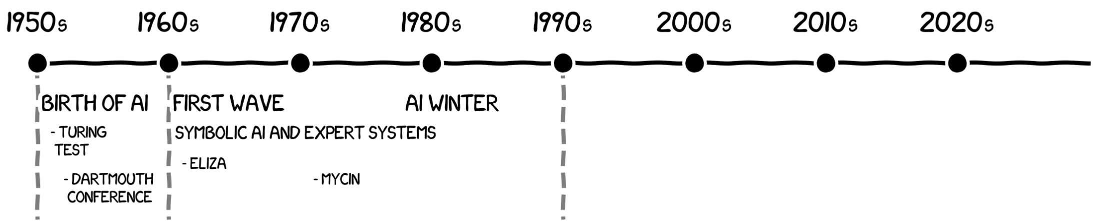
- TURING TEST
- DARTMOUTH CONFERENCE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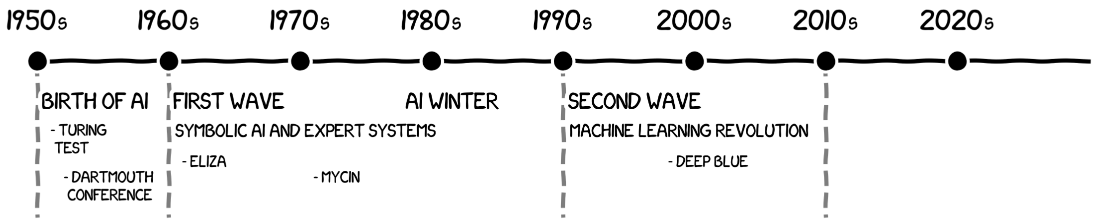
SYMBOLIC AI AND EXPERT SYSTEMS
- ELIZA
- MYCIN
AI WINTER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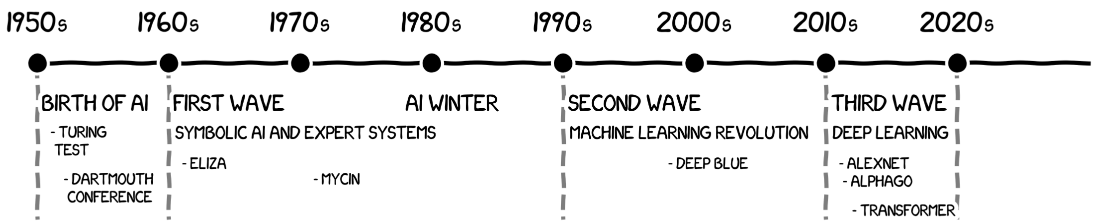
SECOND WAVE
MACHINE LEARNING REVOLUTION
- DEEP BLUE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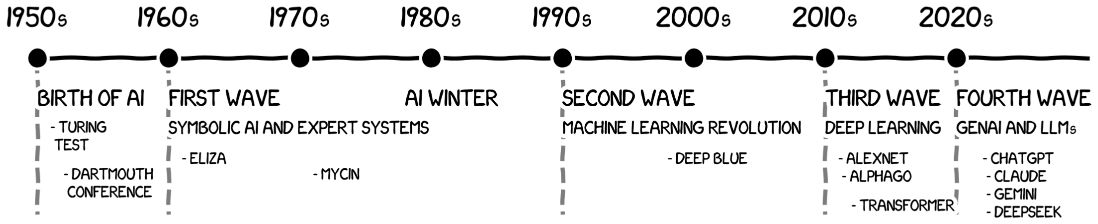
THIRD WAVE
DEEP LEARNING
- ALEXNET
- ALPHAGO
- TRANSFORMER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DEEP LEARNING
- ALEXNET
- ALPHAGO
- TRANSFORMER
FOURTH WAVE
GENAI AND LLMs
- CHATGPT
- CLAUDE
- GEMINI
- DEEPSEEK

History of AI - Main Takeways

1. **Winters**

   Market adjustment from enthusiasm and structural limitations of new tech

> *“The problem of artificial intelligence has vexed researchers for decades. Even simple tasks such as digit recognition—challenges that we as humans overcome so effortlessly—proved extremely difficult to program.”*
>
> *-- Mullainathan & Spiess (2017)*

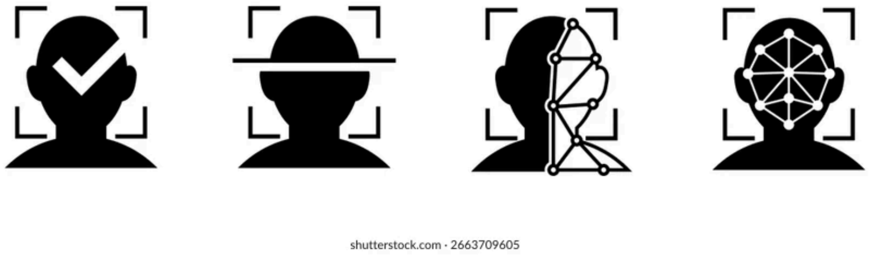
2. **The Machine Learning Revolution**

   Changes in fundamental approaches with the advent of computational power & data

   →**from deduction to induction**

> *"Introspection into how our mind solves these problems failed to translate into procedures. The real breakthrough came once we stopped trying to* ***deduce*** *these rules. Instead, the problem was turned into an* ***inductive*** *one: rather than hand-curating the rules, we simply let the data tell us which rules work best."*
>
> *-- Mullainathan & Spiess (2017)*

Example: Face recognition



No hard-wired rules to scan for certain pixel combinations, based on human understanding of what constitutes a face.

Instead, leverage **large dataset** of photos labeled with a face or not to estimate a function $f(x)$ that predicts the presence y of a face from pixels x.

1.2. The two AI schools

Good Old-Fashioned AI (GOFAI) vs Modern AI

AI Approach	Description	Strengths	Weaknesses
Symbolic AI	Rules, logic, and symbolic reasoning	- Transparency - Interpretability - Computationally light	- Hard to scale - Inflexible (no learning) - Human efforts
Machine Learning	Statistical learning w/ or w/o guidance	- Adaptability - Scalability - Learns w/o predefined rules	- Data & computation power - Opacity (“black box”) - Hidden biases

Key distinction:

- **Symbolic AI**: explicit programming → `If X, then Y`
- **Machine Learning**: implicit programming → `Code how to learn`

Example: Translation

- **Symbolic AI**: Hard-coded grammar rules and mappings between languages.
- **Machine Learning**: Learns linguistic patterns from translated text corpora (e.g., `Google translate`, `GPT`, `BERT`).

1.3. Dominance of Machine Learning

ML's superior performance in key applications

- Image recognition (e.g., facial recognition, medical imaging).
- Natural language processing (e.g., chatbots, voice assistants).
- Financial applications (e.g., risk assessment, fraud detection).

> *"The success of machine learning at intelligence tasks is largely due to its ability to discover complex structures that were not specified in advance. It manages to fit complex and very flexible functional forms to the data* ***without simply overfitting****; it finds functions that work well* ***out-of-sample****."*
>
> *-- Mullainathan & Spiess (2017)*

Classes of ML models

There 3 broad classes of learning: **supervised**, **unsupervised**, **reinforcement**.

1. **Supervised Learning**
   The model learns from **labeled data** (i.e., input-output pairs).
    - **Regression**: learning a continuous value (e.g., stock prices, real estate values).
    - **Classification**: learning a categorical label (e.g., credit approval, fraud detection).

2. **Unsupervised Learning**

   The model learns from **unlabeled data** to find hidden patterns or groupings.

   - **Clustering**: Grouping data points based on similarities (e.g., customer segmentation).
   - **Dimensionality reduction**: Reducing the number of features while preserving the most important information (e.g., PCA).

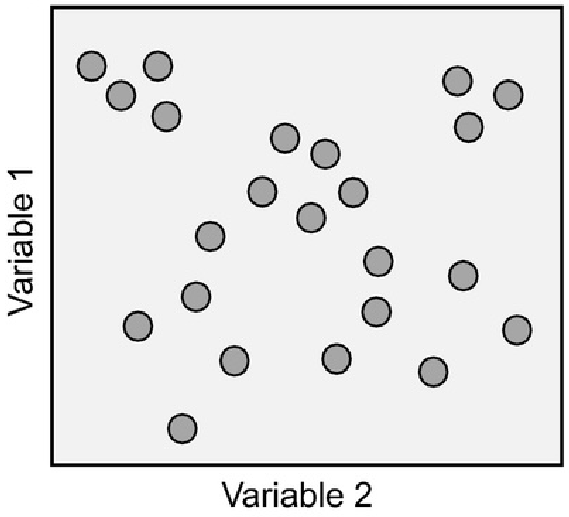
3. **Reinforcement Learning**

   The model learns through interactions with an environment and feedback from its actions.

   - **Algorithmic trading**
   - **Robo-advisor**

Visual intuition

Raw data

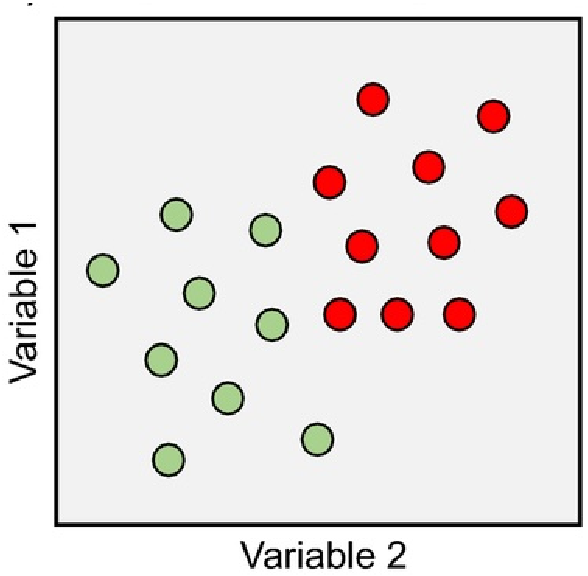


Supervised learning

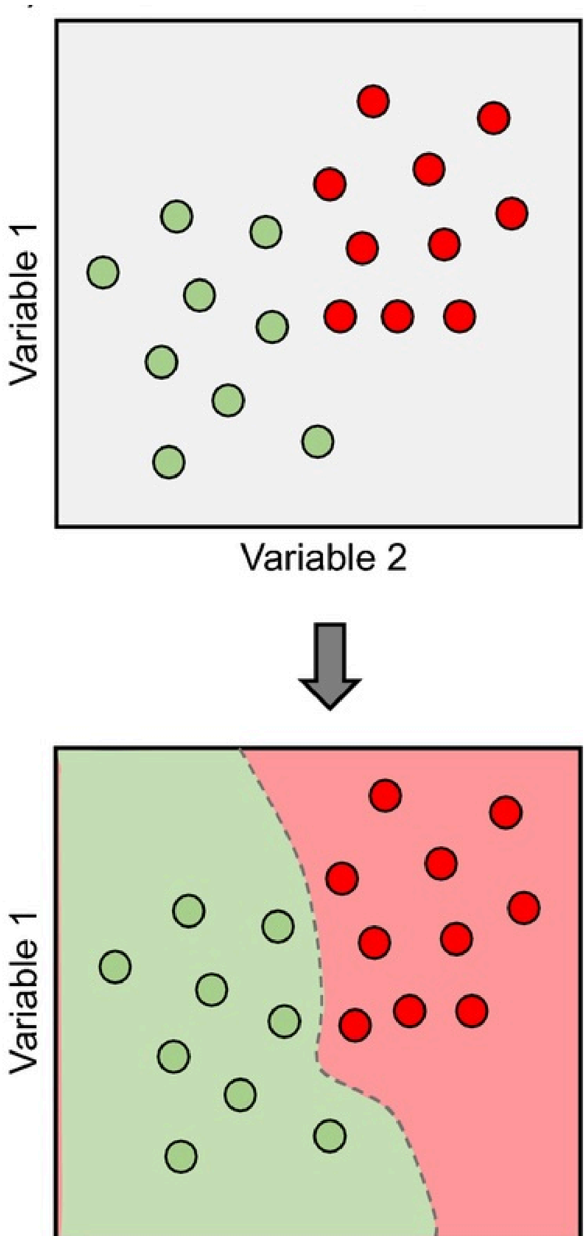
Necessary dimension: **Labelled data**

Supervised learning

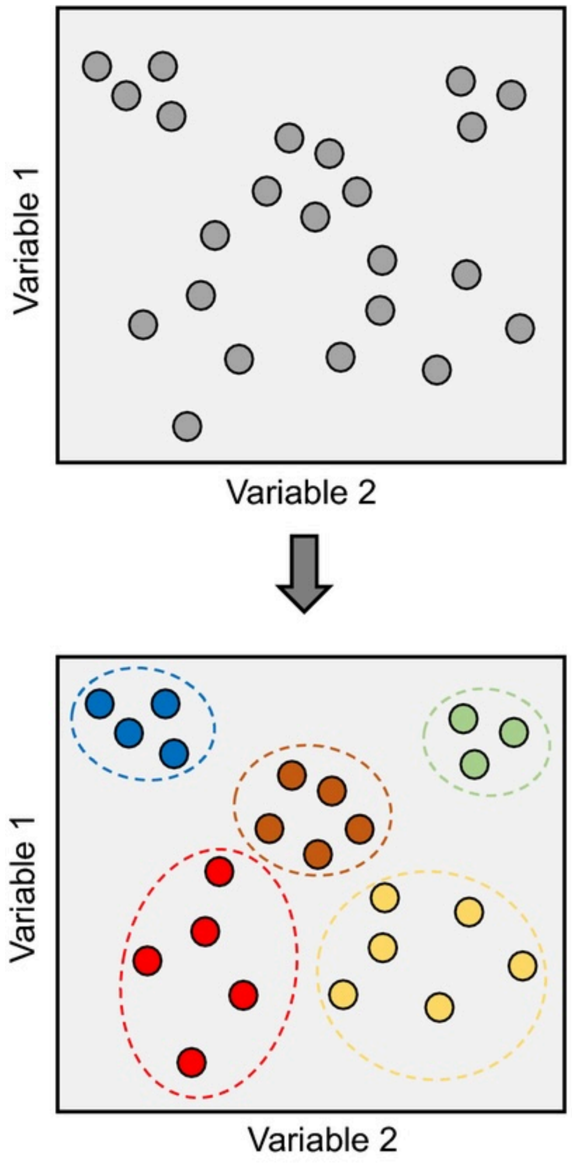
Necessary dimension: **Labelled data**



Supervised learning



Unsupervised learning



Machine Learning Workflow

1. **Problem Definition** (`Prediction`)
2. **Data**
    - Collection
    - Preparation: missing values, encoding of categorical variables, etc.
    - Exploration
    - Feature engineering: select suitable features for the predictions
    - **Split** (see below): training versus evaluation
3. **Learning**
    - Model selection
    - Training
    - Evaluation
    - Tuning
4. **Deployment**

Why ML dominates modern AI?

`Data` and `computation` drive AI progress in Machine Learning

- **Digitalisation of the economy** $\rightarrow$ **data availability** $\uparrow$
  big data, user-generated content, etc.
- Advances in **computing power** and **algorithmic performances**
  cloud computing, GPUs, TPUs, etc.
  deep learning, transformers, etc.

What's the difference with standard econometrics?

Machine learning solves a **different problem**:

Prediction (Y) vs **Estimation** (β):

$$Y = \beta_0 + \beta_1 X$$

- Traditional economic applications: `Estimation`
  →produce good estimates of β to model the relationship between Y and X.

- Machine learning applications: `Prediction`
  → produce a good predictor of Y given X

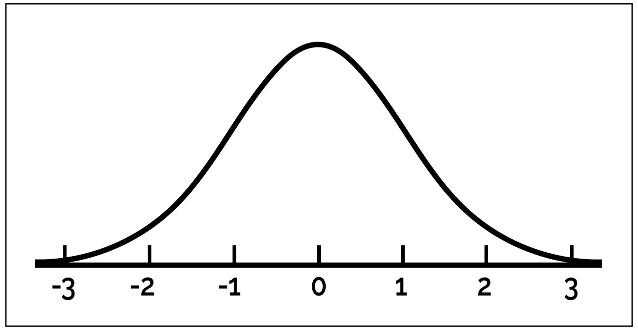
Prediction vs **Causality**

GenAI

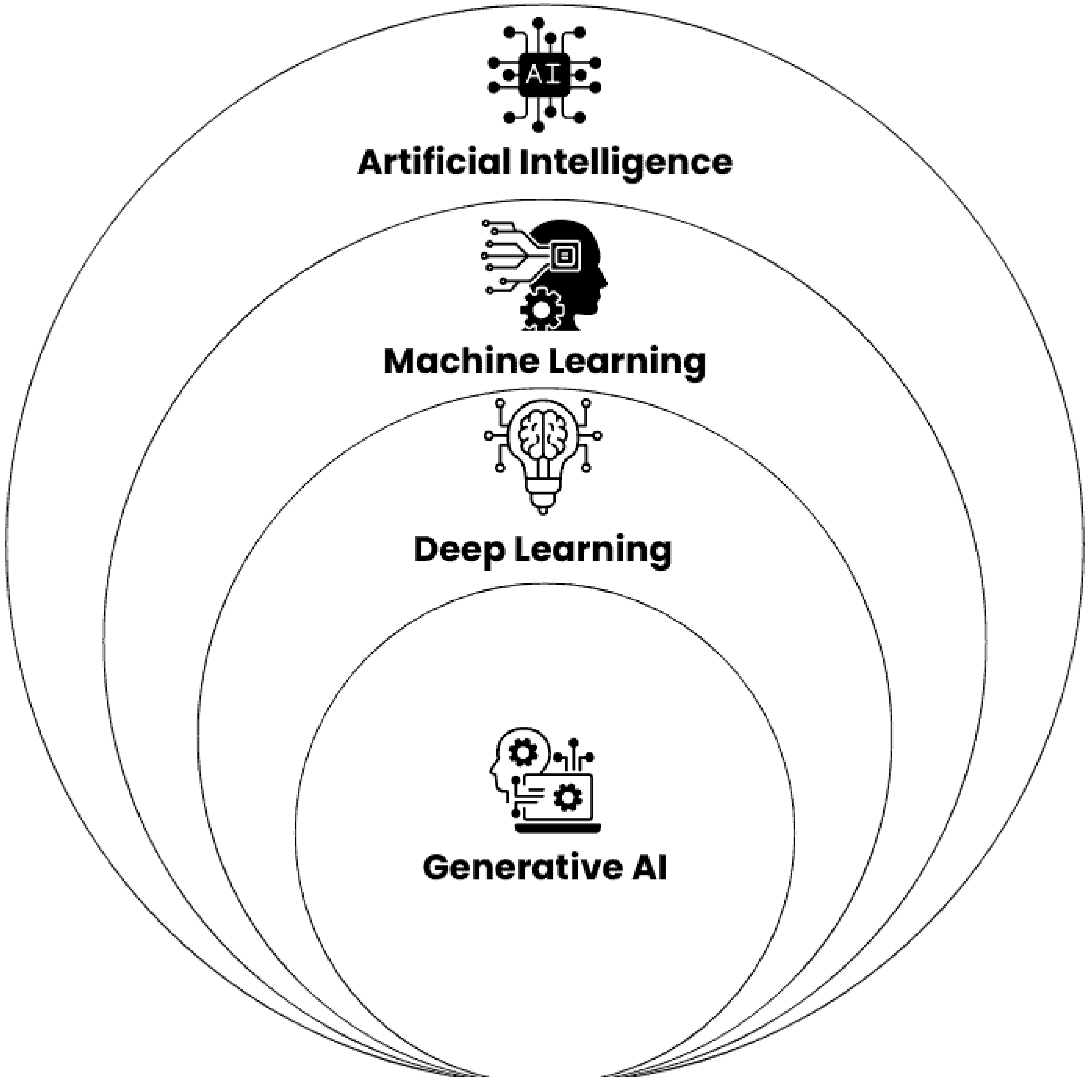
Generative AI (LLMs, GPTs, etc.) builds on the same foundation as traditional machine learning: **learning from data to make predictions**.

Beyond `Prediction`, GenAI **generates new data** (text, images, etc.) by **sampling from the probability distribution learned** for prediction.

In other words:



- Modern machine learning is fundamentally about **prediction**.
    - Prediction involves learning a **probability distribution** over possible outcomes.
- Once this probability distribution is learned, the model can be used not only to predict but also to **generate** new outputs.
    - This is the essence of **Generative AI**: producing new content by **sampling from the learned distribution**.


Artificial Intelligence
Machine Learning
Deep Learning
Generative AI

Limitations remain

- **Explainability problem**: Hard to understand how ML models produce outputs.
- **Data dependency**: Requires large, high-quality datasets.
- **Ethical concerns**: Bias, fairness, privacy issues.

2. Economics of Machine Learning

2.1. The technology of ML

Economics 101: what is a technology?

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A **technology** = a tool that **reduces the cost** of producing some good or service.

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A **technology** = a tool that **reduces the cost** of producing some good or service.

<u>Examples:</u>

- **Steam engine**: $\downarrow$ **cost of transportation and manufacturing**.
- **Printing press**: $\downarrow$ **cost of information dissemination**.
- **Electricity**: $\downarrow$ **cost of mechanical power and lighting**.

What cost does Machine Learning reduce?

What cost does Machine Learning reduce?

Machine Learning reduces <u>the cost of prediction</u>

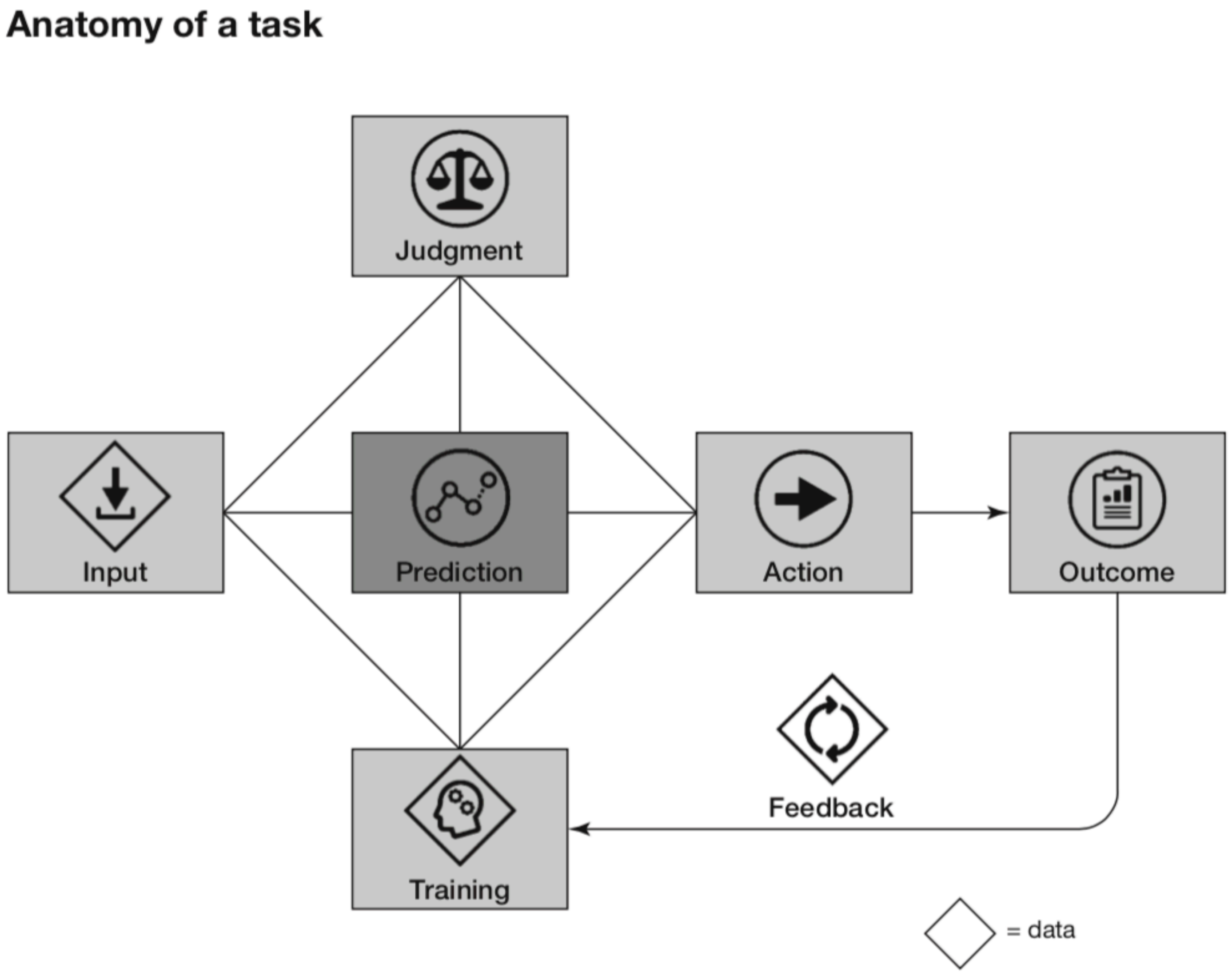
What cost does Machine Learning reduce?

Machine Learning reduces <u>the cost of prediction</u>

- `Prediction` **: infer missing data** (past, present, future).
- **Traditionally expensive** due to:
  - Human expertise (analysts, forecasters).
  - Manual data collection and limited statistical modeling.
  - Limited computing power.

The decision ecosystem

The decision ecosystem



💡 GenAI = Prediction + Action 💡

Complements and substitutes to prediction

Complements and substitutes to prediction

Complements	**Substitutes**
Infrastructure & compute power	Rules-based systems
Data production & access	Traditional prediction models
Human expertise (Causality & Strategy)	Human forecasters & analysts
Ethical & regulatory compliance	Redundant or low-quality data

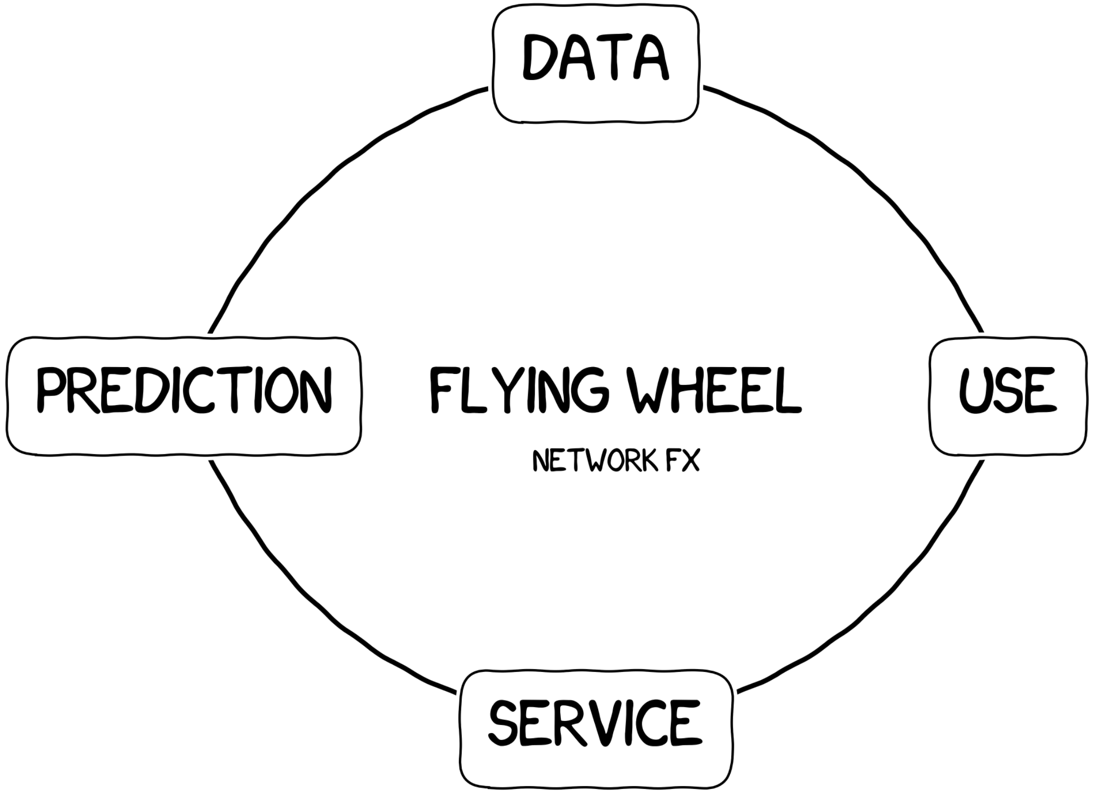
2.2. Key complement to ML: Data

The value of data

1. **Data conditions the growth of Machine Learning**
    - **Existence** of data determines **applicability**
    - **Quality** (labeling) and **quantity** determines **power**

2. **Firms with superior data access** have a significant and self-improving **competitive advantage**.

`Flywheel effect`



The organization of data: production and access

- **Data as a competitive moat:** incumbent firm want **exclusive access** to data
    - **Flywheel & Network effects**
    - **Entry barriers**
    - **Winner-take-all**
- **Data-sharing:** opening data access has trade-offs
    - **Improves competition**
    - **Subject to privacy preferences**
    - **Distorts incentives to produce data**

Regulations and data-production/sharing frameworks shape the economics of **AI development**.

2.3. The limits of ML and "AI snake oil"

Turning problems into `prediction` problems

The Art of Machine Learning:

1. **Reframe** problem as **prediction task**
2. **Find reliable data** sources to improve performance through prediction (historical, alternative, feed, etc.)

Examples:

- **Translation:** Predict the most likely correct translation using same copies of digital books.
- **Self-driving cars:** Predict most likely human action using sensory data.
- **Finance:** Predict likelihood of fraudulent activity using historical transaction data.

Limits of predictions

Not all problems are prediction problems: role of reasoning, causality, or logic.

Not all prediction problems are ML problems: unfit data to perform prediction (e.g., early days of COVID-19)

Symbolic AI vs ML:

- **Symbolic AI** (rule-based) does not need data but lacks adaptability.
- **ML** leverages data but struggles with causality and reasoning.

AI Snake Oil Argument (Arvind Narayanan, 2024)

Some AI solutions are **hyped** but lack real economic value.

Example: AI for job interviews, grant allocation → unreliable and pseudoscientific.

Lesson: AI-ML works best where prediction is

- **Genuinely feasible**: it relies on credible data input
- **Useful**: the prediction environment is not too volatile

3. AI & Finance

3.1. The AI bandwagon

Consultant speach for any `X` industry

- **Efficiency Gains**: *AI automates processes, streamlines operational costs.*
- **Better Decision-Making**: *AI improves risk assessment, document treatment and anomaly detection.*
- **Enhanced Customer Experience**: *Chatbots, personalized recommendations, and automated services.*

... anything specific to finance?

3.2. `Prediction` in finance

Finance is about the **allocation of capital and risk**.

The main barrier to achieving an efficient equilibrium is **<u>information frictions</u>**.

Understanding the role of AI in finance begins with understanding that **every financial innovation—from credit rating to AI or blockchain—is ultimately a response to an information problem**.

The nature of financial information

Financial systems exist because **information is imperfect, incomplete, or costly to obtain**.

Market Friction	Description
Bank runs	Banks **don’t know when** depositors will withdraw their funds.
Asymmetric information	Borrowers **know more** about their ability to repay than lenders.
Adverse selection	Investors **struggle to distinguish** good projects from bad.
Moral hazard	Individuals may **take hidden risks** once insured.
Confidentiality	Companies and citizens may **hesitate to share sensitive information**.

Raison d'etre for **financial contracts, intermediaries, rating agencies, and regulatory frameworks**

→ They exist to manage these frictions, to reduce uncertainty, and to allocate capital more efficiently.

3.3. The impact of AI in finance

Traditional finance

Traditional financial businesses have long relied on **information** to assess risk, allocate capital, and optimize decision-making.

Application Area	Description
Credit scoring & lending	Traditional banks evaluate borrower creditworthiness using **historical financial information**.
Investment advisory	Financial advisors and wealth management firms analyze **market trends** and client **portfolios**.
Trading & market making	Investment banks and hedge funds leverage **proprietary research** and **asset returns** data to execute trades.
Fraud & compliance	Financial institutions analyze **transaction patterns** and **user behavior** to identify **anomalies**, such as unauthorized transactions or money laundering attempts.

The value proposition of AI in Finance

The value proposition of AI in Finance

The **value proposition of Machine Learning in finance** is
to **reduce information frictions** through **superior data-driven prediction**

In modern economies, information is stored in the form of **data**.

→ **Large amounts of data being produced** with relevant signals for **financial** applications:

- digital traces (e.g., transactions),
- investment/trading behavior,
- customer details,
- market signals,
- sensory data (smart wearables, warehouse trackers, etc.),
- social media, etc..

Applying **Machine Learning** to financial applications will leverage such pools of data to improve `prediction`.

Information frictions

Relevant `Prediction` problems everywhere in finance:

- **Incomplete information**: AI <u>may</u> enhance **forecasting** accuracy (**`bank run`**, **`sentiment`**, **`market movements`**)
- **Asymmetric information**: AI <u>may</u> help mitigate issues of:
    - **Screening**: Predict risk of default (**`adverse selection`**).
    - **Monitoring**: Detect anomalous activity (**`moral hazard`**).
- **Obfuscated information**: AI <u>may</u> uncover hidden insights (**`triangulation`**)

Prediction applications

1. Credit Scoring

Predicting default

- **Prediction**: ML predicts likelihood of loan default more accurately than traditional rule-based credit models by identifying complex patterns in borrower behavior.
- **How ML Reduces Cost**:
    - Automates the credit assessment process, reducing manual underwriting costs.
    - Lowers default rates by improving risk assessment.
    - Enables financial institutions to extend credit to underserved customers by analyzing alternative data (e.g., transaction history, utility bill payments).
- **Example**: ML-based credit models allow fintech lenders to approve loans faster while maintaining risk control, increasing financial inclusion.

2. Fraud Detection

Predicting illicit activities

- **Prediction Aspect**: ML predicts fraudulent transactions in real-time by detecting anomalies in spending behavior and transaction patterns.
- **How ML Reduces Cost**:
    - Reduces financial losses from fraud by flagging suspicious transactions before they are processed.
    - Decreases the reliance on manual fraud detection teams, lowering operational costs.
    - Improves customer experience by reducing false positives in fraud detection systems.
- **Example**: ML-based fraud detection systems in credit card transactions use anomaly detection to prevent unauthorized transactions, reducing fraud-related losses for banks and consumers.

3. Algorithmic Trading

Predict market movements and best-responses

- **Prediction Aspect**: ML models analyze historical market data, news sentiment, and macroeconomic indicators to predict asset price movements and execute trades accordingly.
- **How ML Reduces Cost**:
    - Minimizes human error and emotional biases in trading decisions.
    - Reduces the need for large trading teams by automating strategy execution.
    - Optimizes trade execution, reducing slippage and transaction costs.
- **Example**: Hedge funds and proprietary trading firms use reinforcement learning models to develop adaptive trading strategies that dynamically adjust to changing market conditions, improving profitability.

4. Customer Service

Predict customer needs

- **Prediction Aspect**: ML predicts customer inquiries and automates responses through Natural Language Processing (NLP), reducing the need for human intervention.
- **How ML Reduces Cost**:
    - Cuts customer support expenses by replacing human agents with AI-powered chatbots.
    - Reduces response time, improving customer satisfaction and retention.
    - Allows 24/7 customer service at a fraction of the cost of human-operated call centers.
- **Example**: AI-powered virtual assistants like Erica (Bank of America) and Cleo help customers check balances, track expenses, and receive financial recommendations, lowering operational costs for banks while enhancing user experience.

Everyone is after it

- **Incumbents** leveraging data access (banks, payments, insurance, asset managers, etc.)
- **Newcomers** exploiting new data opportunities

Trends

Lending

- **Traditional banking**: AI is used to refine profiling and pricing of loan products
    - `JPMorgan Chase` 1st in AI Evident Index.
- **New businesses**:
    - **Fintech lending** platforms incorporate **alternative data** for credit scoring
        - **`Rocket Mortgage`** for mortgages
        - **`Upstart`** for personal/car loans
        - **`Klarna`** for BNPL
    - **Peer-to-peer lending** platforms leverage AI-driven risk assessment models
        - **`LendingClub`**, **`Prosper`**
    - **BigTech lending** leveraging activity data on the platform
        - **`Amazon`**

Investment

- **Wealth management**: **Robo-advisors** apply machine learning to portfolio management and asset allocation
    - `Betterment` for financial advice
    - `Wealthfront` for automated investing
- **Crowdfunding**: AI enhances risk assessment in crowdfunding platforms
    - `Kickstarter`, `Seedrs`

Trading

- **Algorithmic trading** uses AI for **market-making** and **high-frequency trading**
  - `Renaissance Technologies`, `Citadel Securities`
- AI-driven **sentiment analysis** interprets news, reports, and social media for trading insights
  - `Kavout`

Fraud Detection & Compliance

- AI models identify patterns of **fraudulent transactions** in real-time
    - `Visa`, `Mastercard`
- AI supports **compliance** efforts in areas such as **AML** (Anti-Money Laundering) and **KYC** (Know Your Customer)
    - `ComplyAdvantage` for AML
    - `Feedzai` for fraud

4. Challenges at the AI frontier

4.1. Information barriers

- **Trade-off between data sharing & privacy**: Incentives to share vs. risk of exposure.
- **Data ownership & control**: Who owns financial data—customers or firms?

Open Data policies

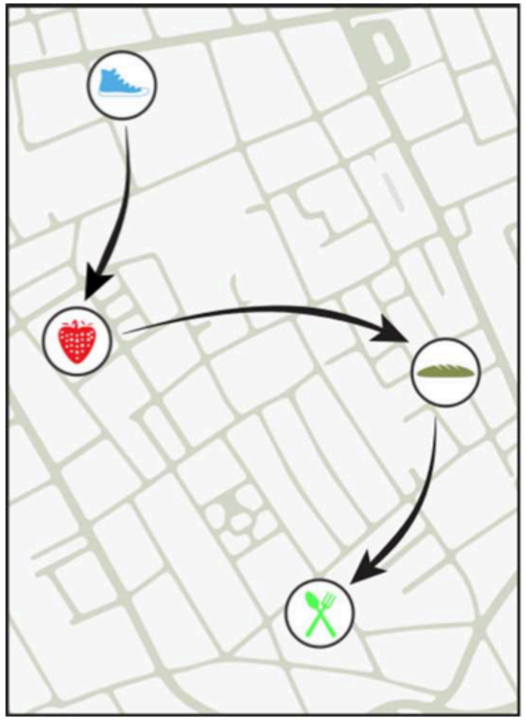
- **Open Banking & Open Finance**: Expanding access to financial data.
- **Costs vs. benefits**: Interoperability challenges, regulatory hurdles, incentives to innovate.
- **Compatibility issues**: Ensuring seamless integration of AI across financial institutions.

4.2 Ethics and fairness

- **Data-path dependencies and embedded biases**

Joy Buolamwini, 2023 - *Unmasking AI: My Mission to Protect What Is Human in a World of Machines*

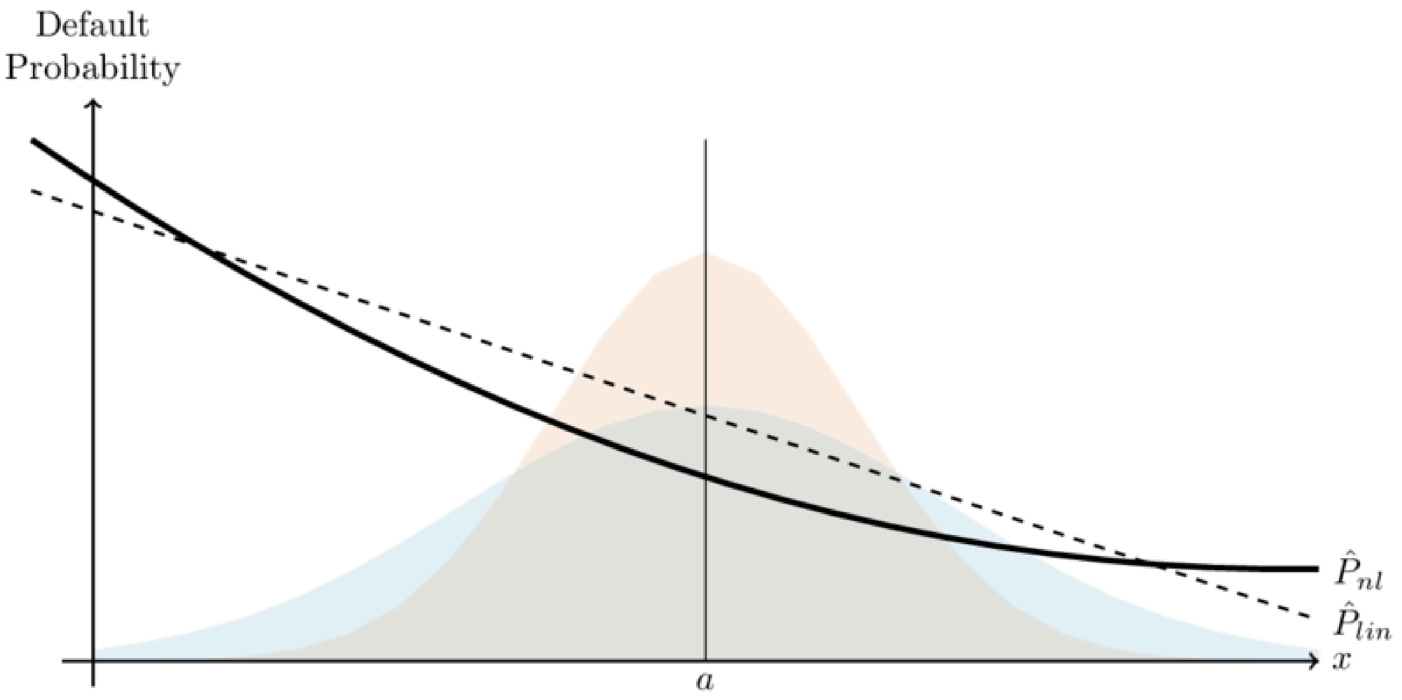
- **Triangulation**
  Yves-Alexandre de Montjoie et al. - *Unique in the shopping mall* - Science, 2015



shop	user_id	time	price	price_bin
	7abc1a23	09/23	$97.30	$49 – $146
	7abc1a23	09/23	$15.13	$5 – $16
	3092fc10	09/23	$43.78	$16 – $49
	7abc1a23	09/23	$4.33	$2 – $5
	4c7af72a	09/23	$12.29	$5 – $16
	89c0829c	09/24	$3.66	$2 – $5
	7abc1a23	09/24	$35.81	$16 – $49

- **Winners and losers of AI adoption**: improving prediction technology has both extensive and intensive margin effects

Fuster et al. - *Predictably unequal?* - Journal of Finance



4.3. Toxic data

- **Turing's nightmare**: AI-generated content may contaminate original data.
- **Contribution halt**: AI-usage may block the natural human production of data
    - Acemoglu et al., 2025: Wikipedia activity drop after ChatGPT
- **AI Model Collapse**: Chained dependence on flawed data may amplify error and destroy information value.
    - Shumailov et al., 2024
    - Georg and Roukny, 2025
- **Watermarking data**: Preventing AI-generated content from contaminating financial data.

4.4. Agentic AI

- **Autonomous AI agents**: When decision is coupled with predictions.
- **Flash crashes & AI-driven volatility**: Historical examples of AI-induced market instability.
- **Algorithmic collusion**
    - Calvano et al., 2020 - *Artificial Intelligence, Algorithmic Pricing, and Collusion* - American Economic Review
- **AI Alignment**

5. Policy and Regulation

Why Policy and Regulation Matter

Regulation must evolve with technology — from Basel I (credit risk) to DORA, MiCA, and now the **AI Act**.

- AI and ML transform **how financial intermediation** operates: who holds information, how risk is priced, how accountability is ensured.
- Traditional prudential, conduct, and market integrity frameworks were designed for *human* decision-making.
- ML introduces new **information frictions**: opacity, data dependence, feedback loops.
- Regulators now face questions of **explainability, accountability, and fairness**.

Recent Policy Efforts on AI in Banking

1. EU Artificial Intelligence Act (2024)

- First comprehensive **AI regulation** globally.
- **Risk-based approach**: minimal, limited, high, and unacceptable risk categories.
- Financial services (e.g., credit scoring, insurance underwriting) are **“high-risk”**.
- Requires:
    - Human oversight and transparency
    - Data quality and bias controls
    - Robust documentation and governance
- Entered into force **1 August 2024**; high-risk rules phase in by **2026**.

Implication for banks: ML credit models, robo-advice, and AML monitoring now fall under AI compliance regimes.

2. **European Banking Authority (EBA) – Special Topic on AI (2024/2025)**

- EBA mapped AI use across EU banks:
  - Regression, decision trees, NLP, neural networks.
  - ~40% already using **General-Purpose AI (GPAI)**.
- Focus areas:
  - Governance and validation of models.
  - Explainability and internal control functions.
  - Supervisory coordination under the EU AI Act.
- Lays groundwork for **supervisory expectations** on AI model risk.
  - Embeds AI into the prudential supervision toolkit.

3. **Financial Stability Board (FSB) – Global Monitoring (2024)**

- Report: *“Monitoring Adoption of Artificial Intelligence and Related Risks.”*
- Highlights systemic risks:
    - Concentration in third-party providers (e.g., cloud, data).
    - Model risk and correlated errors.
    - Cyber and operational dependencies.
- Encourages jurisdictions to align AI risk management with financial stability objectives.

Takeaway: AI regulation extends beyond conduct — it’s a **macroprudential issue**.

4. ESMA Supervisory Statement (May 2024)

- Investment firms and banks **remain fully responsible** for AI decisions.
- No delegation of accountability to algorithms.
- Requires governance documentation and model explainability.

Principle: *"Responsibility cannot be outsourced to AI."*

Mapping Policy Objectives to AI Challenges

Objective	AI-Driven Challenge	Regulatory Response
Financial stability	Algorithmic risk & model drift	FSB monitoring, Basel governance
Consumer protection	Bias in credit scoring	EU AI Act, FEAT, GDPR
Market integrity	Manipulative algorithms	MiFID II, ESMA guidance
Operational resilience	Cloud & model dependency	DORA
Competition & data concentration	BigTech data dominance	Open Data / PSD3 proposals

Common Policy Themes

- **Accountability:** Human oversight for algorithmic decisions.
- **Explainability:** Transparent and auditable models.
- **Fairness:** Avoid bias in data-driven decisions.
- **Data governance:** Secure, lawful, and interoperable data use.
- **Cross-border consistency:** Prevent regulatory arbitrage.

Regulation of AI is regulation of **information governance**.