The History of Artificial Intelligence

A Brief Overview

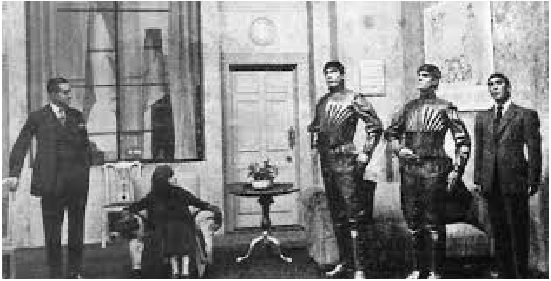
Dr. Lama Tarsissi

07 August 2025

Outline

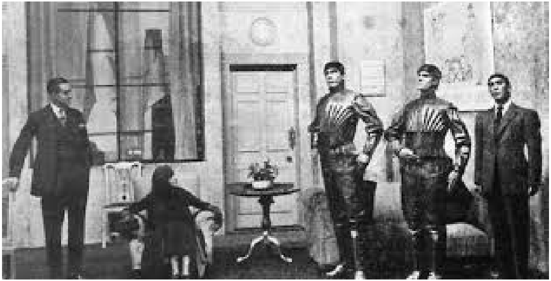
1. Early Concepts
2. Birth of AI
3. AI Winter and Revival
4. Modern AI
5. Future of AI

Early Concepts (Pre-1950s)



- 1921: Karel Čapek's play *R.U.R.* (Rossum's Universal Robots, subtitled in English from the Czech book *Rossumovi univerzální roboti*) introduces the term "robot."

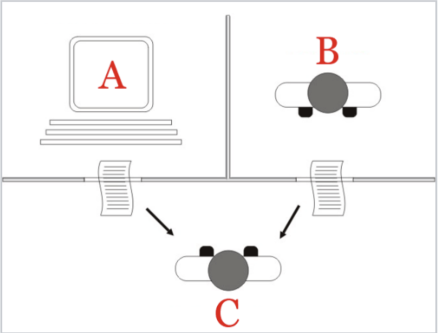
Early Concepts (Pre-1950s)



- 1921: Karel Čapek's play *R.U.R.* (Rossum's Universal Robots, subtitled in English from the Czech book *Rossumovi univerzální roboti*) introduces the term "robot."
- 1943: Warren McCulloch and Walter Pitts model neural networks, laying groundwork for AI. (No hidden layers, 1 input–>10 outputs)

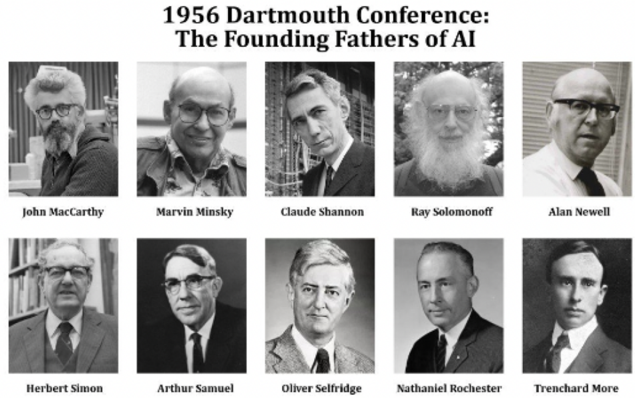
- 1950: Alan Turing proposes the Turing Test to evaluate machine intelligence.
- Formalizes the AI by replacing the question, **"Can machines think?"** by creating a game called **"imitation game"** to distinguishing if an answer is given by a human or not.
- Compare the situation to Chatgpt nowadays...

Alan Turing, 1936 (Source: Wikimedia Commons)



The "standard interpretation" of the Turing test, in which player C, the interrogator, is given the task of trying to determine which player – A or B – is a computer and which is a human. The interrogator is limited to using the responses to written questions to make the determination.[1]

Birth of AI (1950s-1980s)



- 1956: Dartmouth Conference, led by John McCarthy, coins the term "Artificial Intelligence."

- 1960s: Early AI programs like ELIZA (1964)(natural language processing) and SHRDLU (1968)(problem-solving).

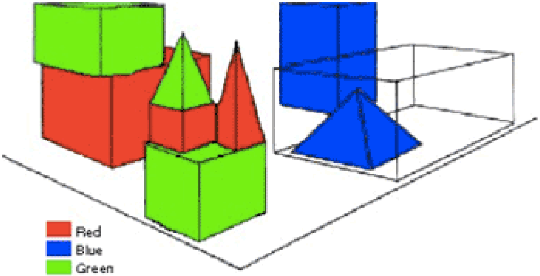
Vintage computer

```
  Welcome to
                    EEEEEE  LL      IIII   ZZZZZZ   AAAAA
                    EE      LL       II       ZZ   AA   AA
                    EEEEE   LL       II     ZZZ    AAAAAAA
                    EE      LL       II    ZZ      AA   AA
                    EEEEEE  LLLLLL  IIII ZZZZZZ    AA   AA

  Eliza is a mock Rogerian psychotherapist.
  The original program was described by Joseph Weizenbaum in 1966.
  This implementation by Norbert Landsteiner 2005.


ELIZA: Is something troubling you ?
YOU:   Men are all alike.
ELIZA: What is the connection, do you suppose ?
YOU:   They're always bugging us about something or other.
ELIZA: Can you think of a specific example ?
YOU:   Well, my boyfriend made me come here.
ELIZA: Is it important to you that your boyfriend made you come here ?
YOU:   He says I'm depressed much of the time.
ELIZA: I am sorry to hear that you are depressed.
YOU:   It's true. I am unhappy.
ELIZA: Can you explain what made you unhappy ?
YOU:
```

- ELIZA is an early natural language processing computer program developed from 1964 to 1967 at MIT by Joseph Weizenbaum



Person: Pick up a big red block.

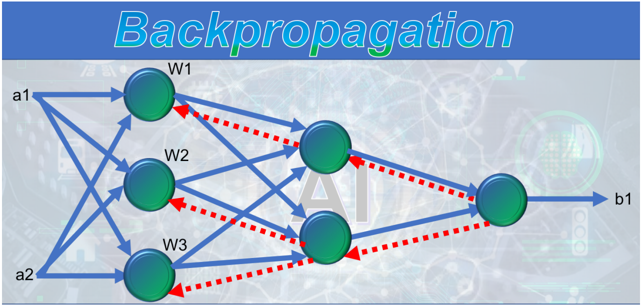
Computer: OK.

Person: Grasp the pyramid.

Computer: I don't understand which pyramid you mean.

- SHRDLU is a program for understanding natural language, written by Terry Winograd at the M.I.T. Artificial Intelligence Laboratory in 1968-70.

- 1969: Minsky-Papert "Perceptrons" mention that neural network have limits, which was a wrong interpretation of the book
- 1980: Expert systems boom, with AI applied in medicine and finance. (succession of rules and steps)
- 1986: The "Backpropagation" rule is introduced by G.Hinton et al.



AI Winter and Revival (1990s-2010s)

- Late 1990s: AI Winter due to overhyped expectations and limited computing power.
- 1997: IBM's Deep Blue defeats chess champion Garry Kasparov.
- 2000s: Machine learning gains traction with improved algorithms and data availability.

G. Kasparov vs. IBM Deep Blue

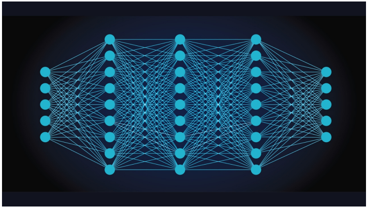
AI Winter and Revival (1990s-2010s)

AI Winter and Revival (1990s-2010s)

N.B:1990, Y.Lecun Automated cheque reader (10%)- 1998, Convolutional neural network Y.Lecun (not fully connected)

Modern AI (2010s-Present)

- 2012: AlexNet by G.Hinton et al. **revolutionizes** deep learning.
- 2016: AlphaGo by DeepMind defeats world champion Go player Lee Sedol.
- 2020s: Large language models (e.g., GPT-3, Grok) and generative AI (stable diffusion, midjourney,..) transform industries.



Neural network

Future of AI

Autonomous vehicle

- Ethical AI: Focus on fairness, transparency, and accountability.

Future of AI

Autonomous vehicle

- Ethical AI: Focus on fairness, transparency, and accountability.
- General AI: Pursuit of machines with human-like intelligence.

Future of AI

Autonomous vehicle

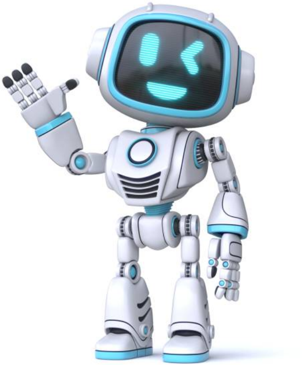
- Ethical AI: Focus on fairness, transparency, and accountability.
- General AI: Pursuit of machines with human-like intelligence.
- Integration: AI in healthcare, autonomous vehicles, and more.

Conclusion

From early neural network models to today's generative AI,
the history of AI reflects human ingenuity and ambition.

What's next for AI?

Thank You



Questions?

Thank you for your attention!

IA and Deep Learning

Introduction

Dr. Lama Tarsissi

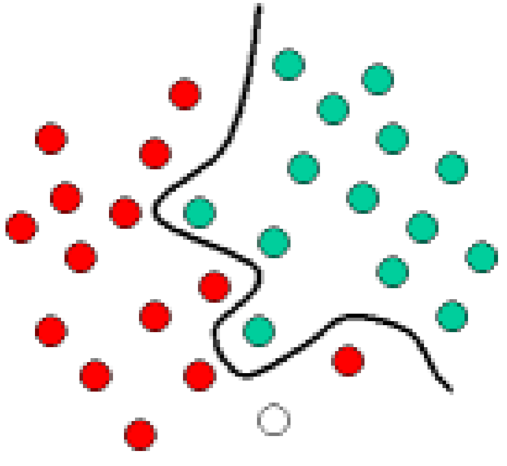
Machine Learning

Automatic Learning

- **Objective →** Learning knowledge from **data**

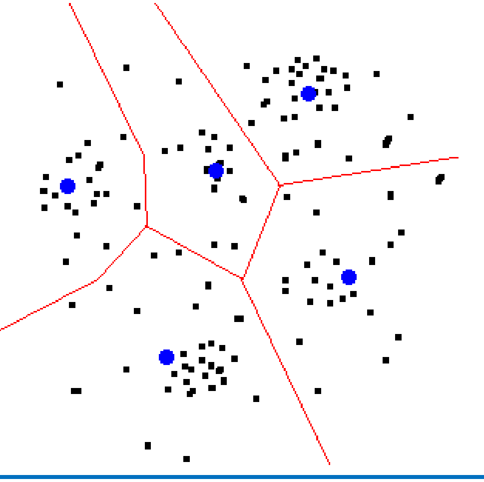
Supervised learning

Data *= observations + tags*
Knowledge → *relation input-output*



Un-supervised learning

Data *= observations*
Knowledge → *latent structures*



Supervised learning(1/2)

- From a number of examples …

input (data)	4	13	6	11	8
output (class label)	0	1	0	1	0

- … we want to find a hypothesis that explains the examples.

question	7
prediction	?

Possible hypotheses

- *Even numbers*
- *Numbers greater than 10*

Supervised learning(2/2)

- By adding new examples…

input (data)	4	13	6	11	8	2
output (class label)	0	1	0	1	0	1

- … the space of hypotheses is reduced!

question	7
prediction	?

Possible hypotheses

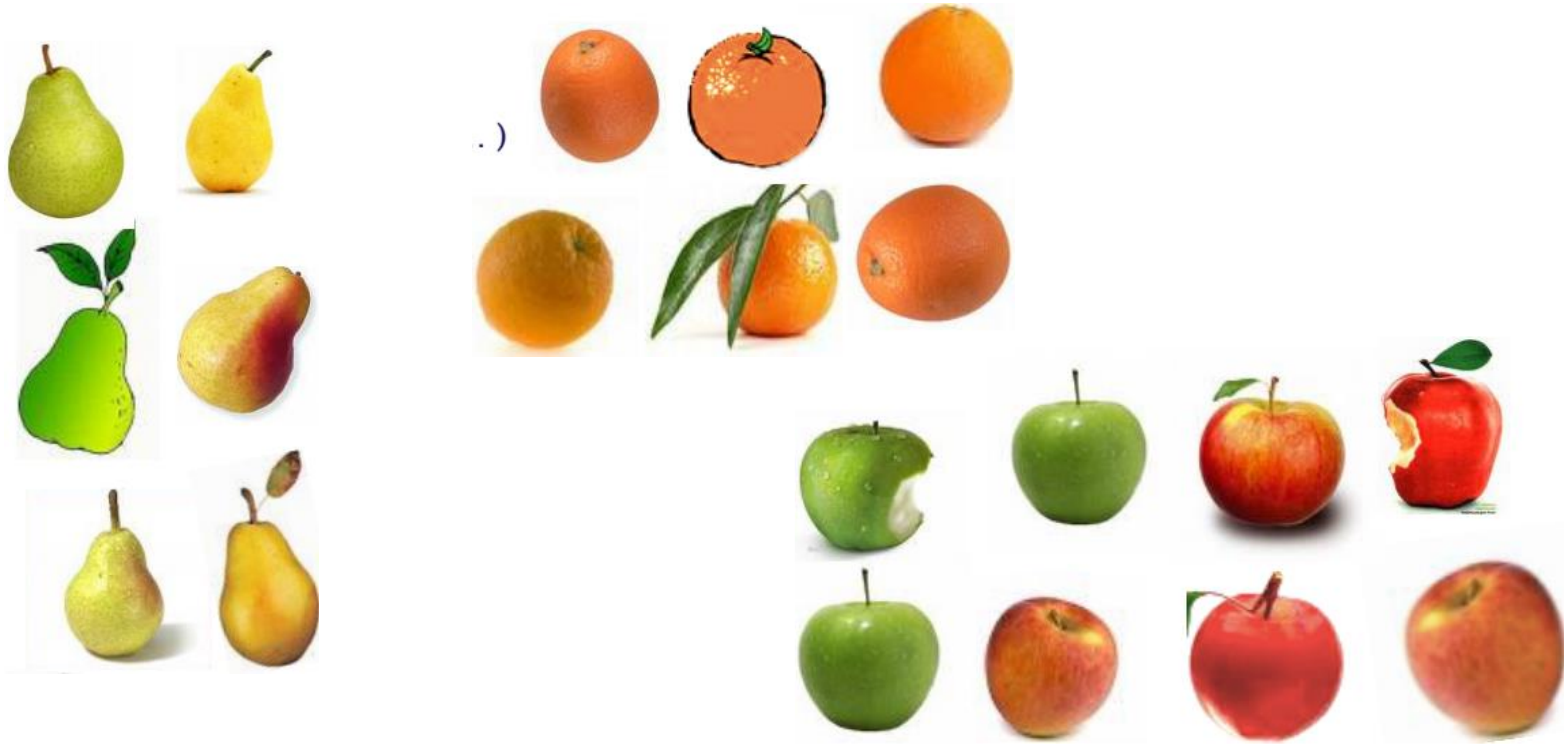
- ~~*Even numbers*~~
- ~~*Numbers greater than 10*~~
- *Prime numbers*

Unsupervised learning (1/3)

- From a set of data (without the correct answers)…

Unsupervised learning (2/3)

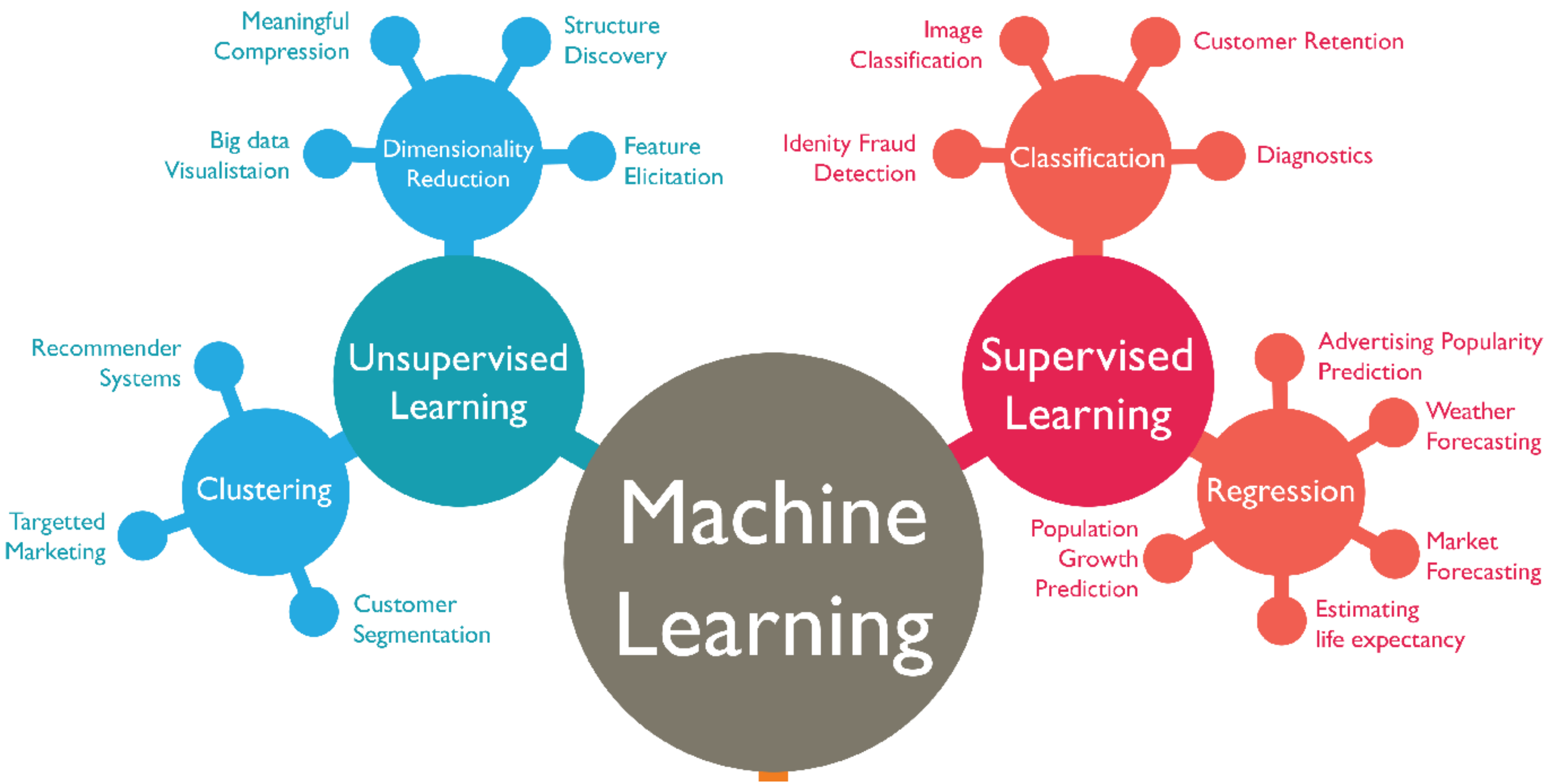
- … we want to form groups respecting a similarity criterion



Unsupervised learning(3/3)

- **Challenges**
  - *What similarity criterion ?*
  - *How many groups ?*

Types of learning



An example of learning

First of all, DATA

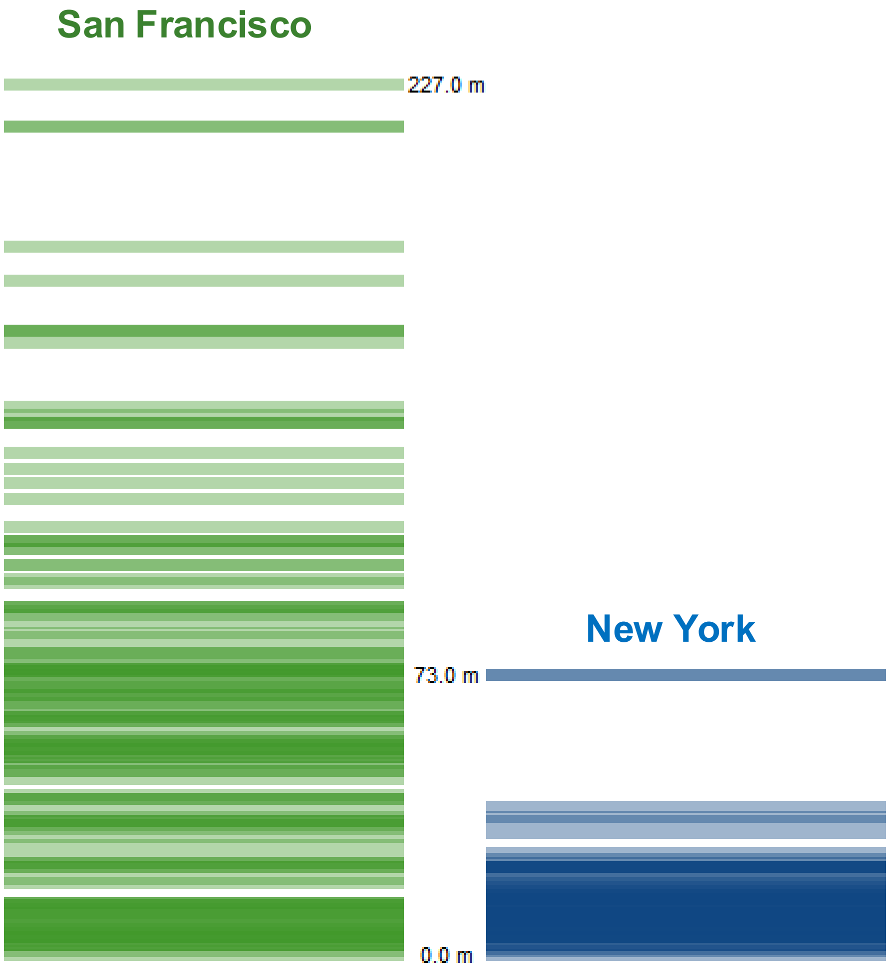
- **Data**
  - *Characteristics of the apartments in **New York** and **San Francisco***

Altitude (m)	Year	Rooms	m2	Total price	Price / m2	City
10	2005	2	50	500'000	10'000	NY
125	1998	1	45	600'000	13'000	SF
…	…	…	…	…	…	…

- **Problem**
  - *Based on the characteristics of an apartment...*
  - *...predict whether it's in New York or San Francisco*

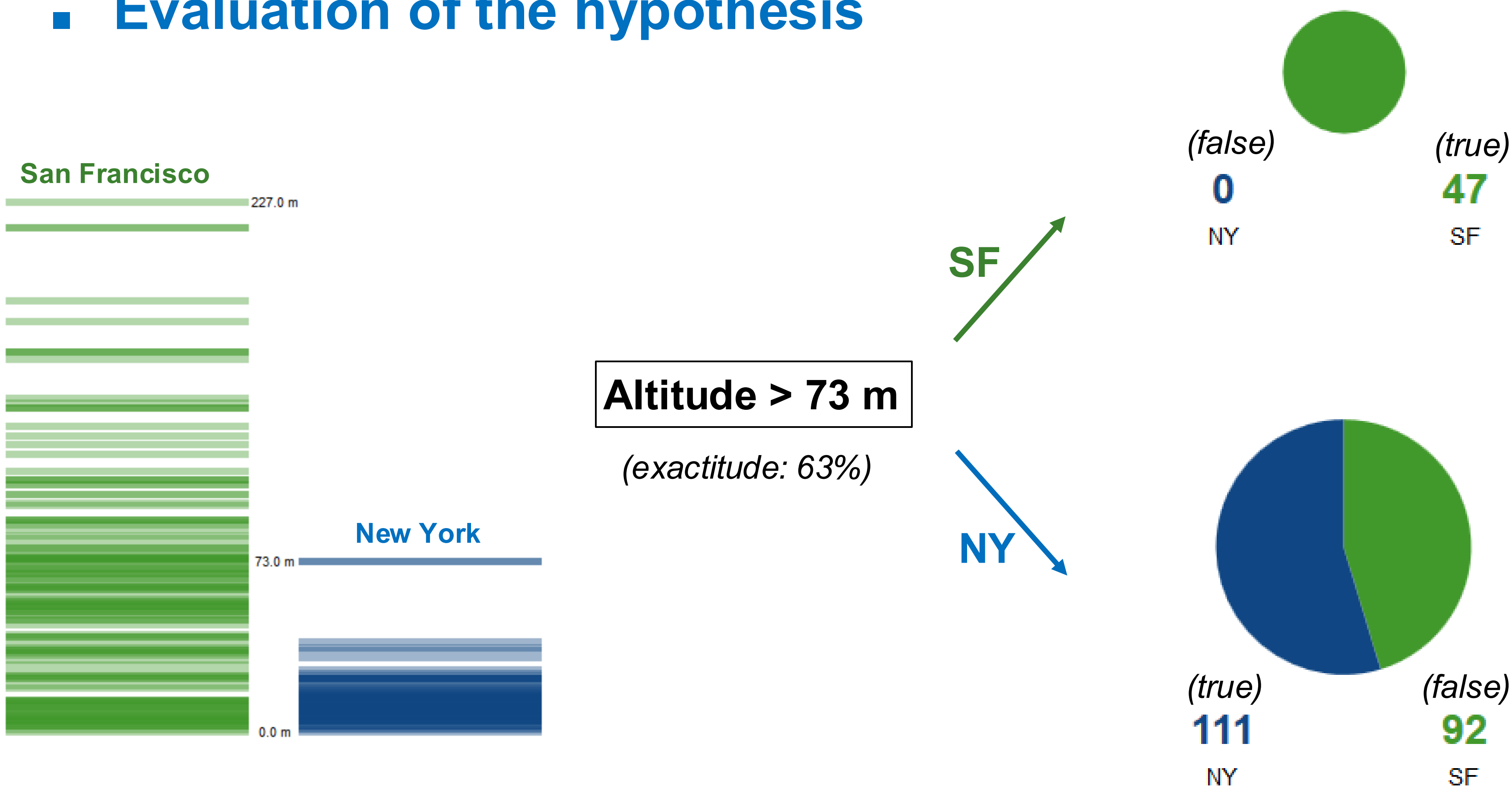
A little intuition

- **First Hypothesis**
  - *Since San Francisco is rather hilly, an apartment's elevation seems to be a good way to distinguish between the two cities.*
  - *Based on the data, we could decide that an apartment above 73 meters should be classified as located in San Francisco.*



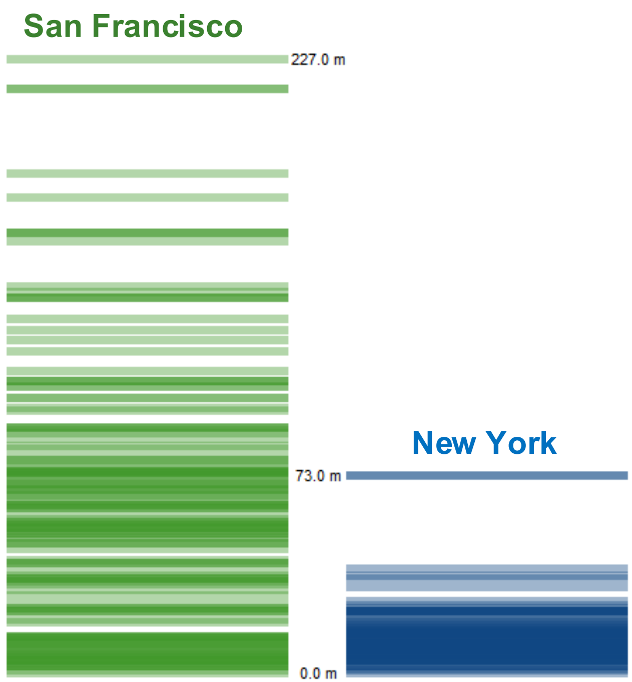
The errors of prediction

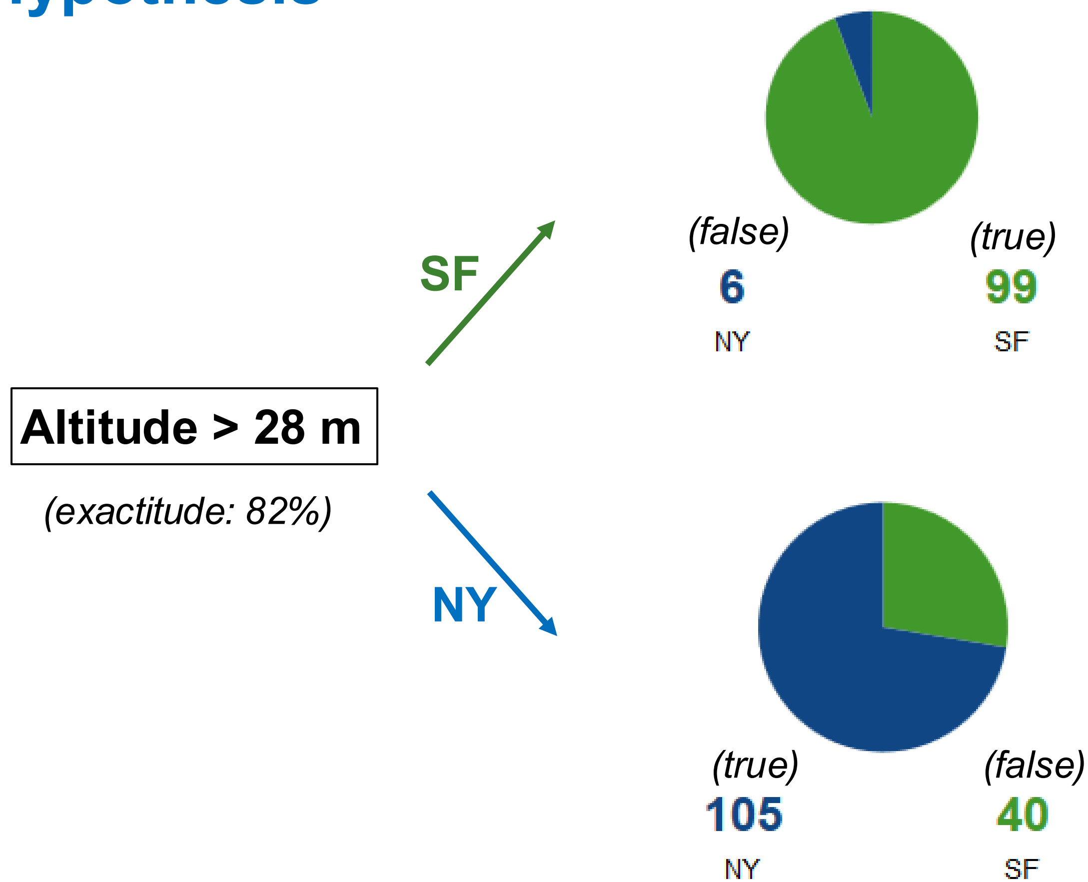
- **Evaluation of the hypothesis**



The best seperation point

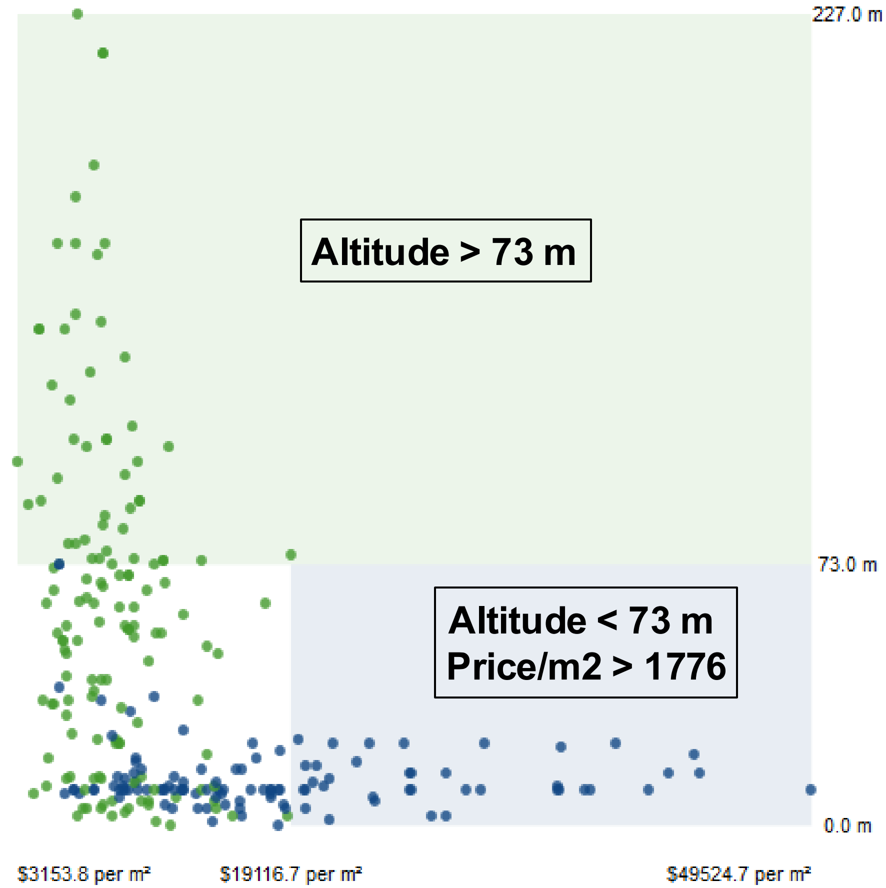
- **Correction of the hypothesis**





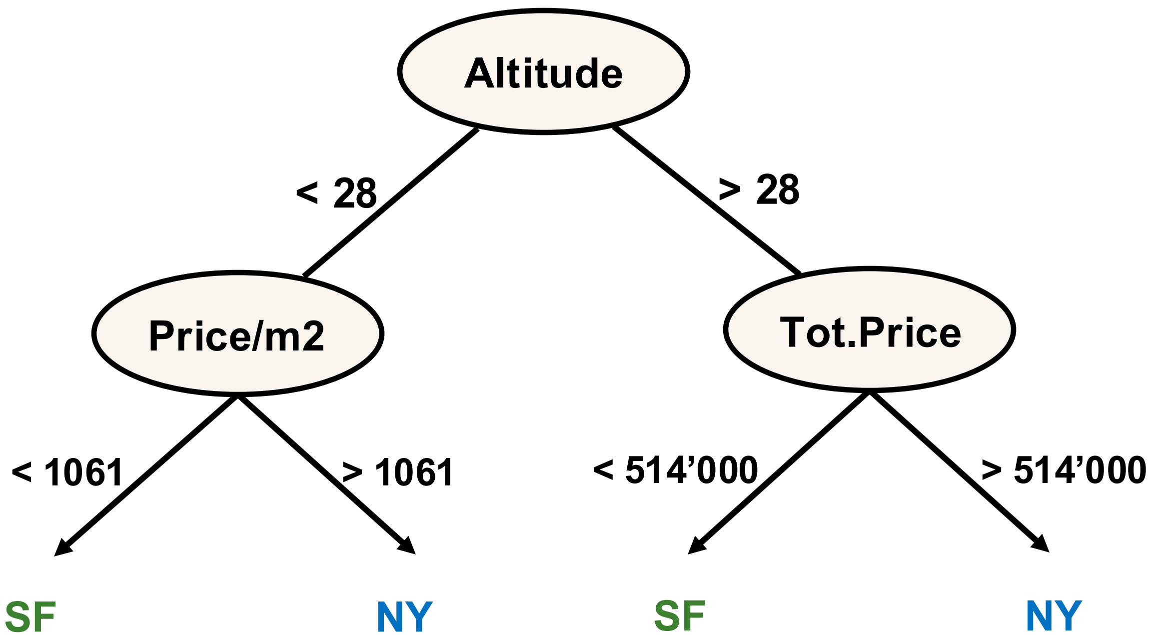
A new perspective

- **Add other dimensions**
  - *Adding information other than altitude allows for nuance.*
  - *For example, New York apartments can command very high prices per square meter.*
  - *Thus, by visualizing altitude and price per square meter with a scatter plot, we can better differentiate between houses located at lower altitudes.*



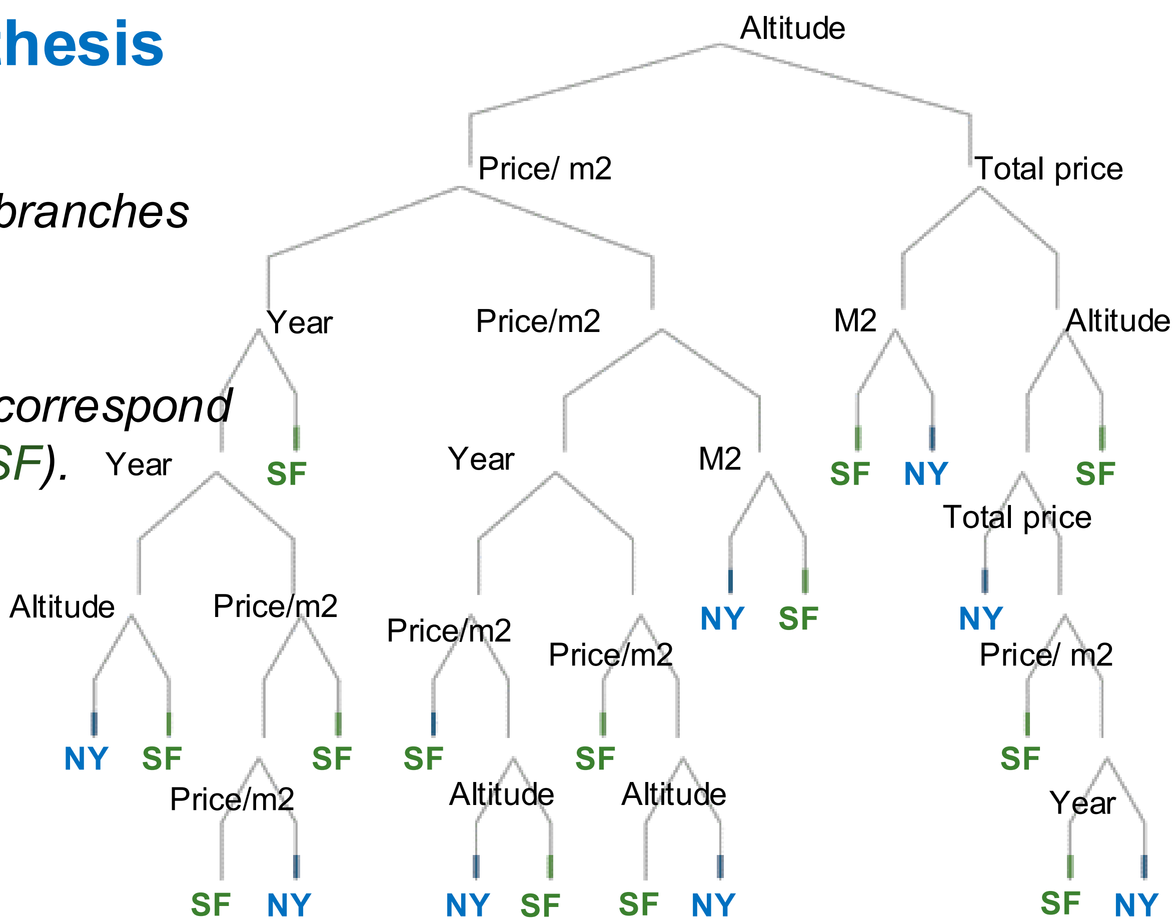
Get a better prediction

- **New hypothesis**
  - *Additional branches help improve prediction*



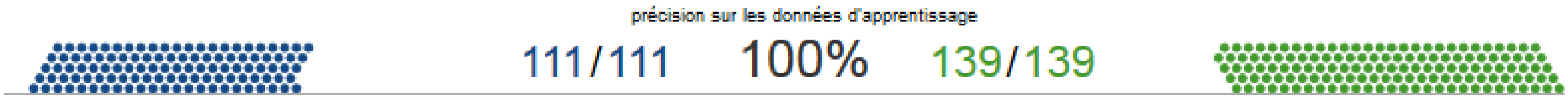
Growing a decision tree

- **Hierarchical hypothesis**
  - *You can add as many branches as needed.*
  - *The leaves of the tree correspond to a prediction (NY or SF).*



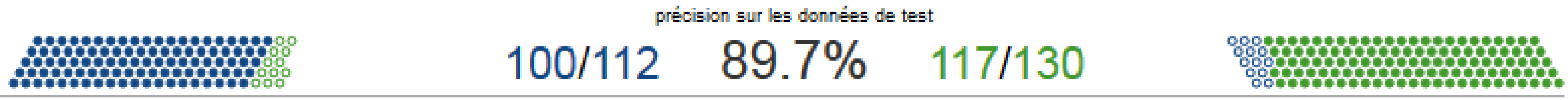
Training data

- **Prediction**
  - *The decision tree determines where an apartment is located by traversing the branches corresponding to the data.*
  - *This data is called training data because it was used to train the model. This is done automatically by an algorithm.*
  - *The resulting tree perfectly predicts the training data because it was built on this data.*

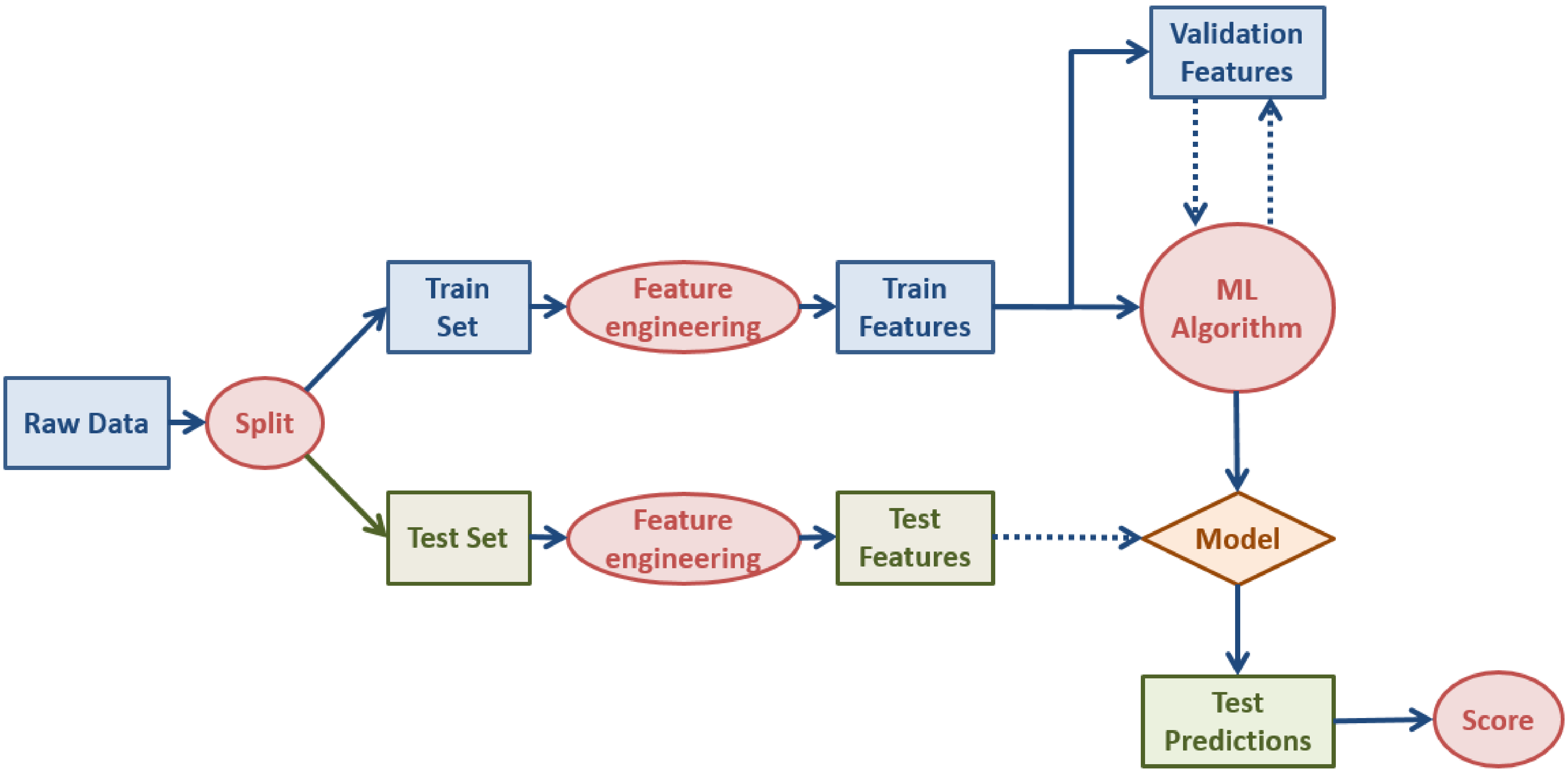


Confronting reality

- **Evaluation**
  - *Obviously, what matters is the tree's accuracy in making predictions for previously unseen data.*
  - *To evaluate the performance of our prediction model on new data, we need to apply it to previously unseen data. This data is called test data.*
  - *The quality of a prediction model is measured on the* ***test data****, not the training data.*



General learning plan



Quiz

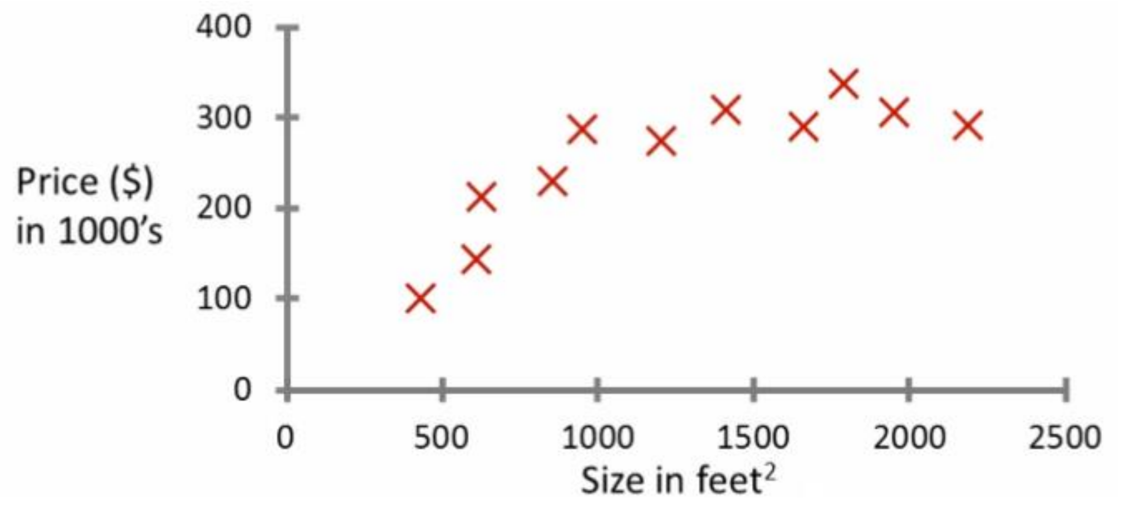
- You want to develop learning methods to solve the following problems.
  1. *You have a large inventory of identical items. You want to predict how many of these items will sell over the next 3 months.*
  2. *You need to review your customer accounts and determine whether each one has been hacked or compromised.*

- Are they regression or classification problems?
  A. *Problem 1 → classification - Problem 2 → classification*
  B. *Problem 1 → classification - Problem 2 → regression*
  C. *Problem 1 → regression - Problem 2 → classification*
  D. *Problem 1 → regression - Problem 2 → regression*

The problem of over-fitting

Choice of the model (1/5)

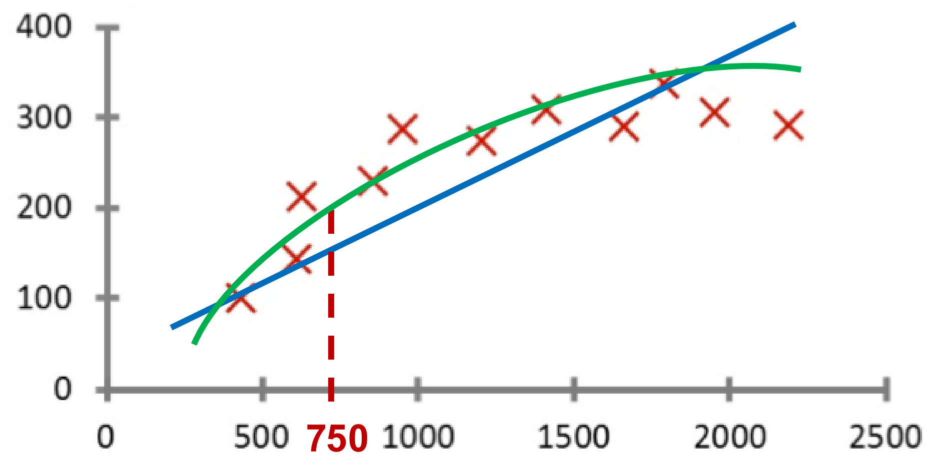
- PROBLEM → A friend has a 750 sq ft house
  - *What price could he get for his house...*
  - *... knowing the prices of a few other houses in the neighborhood?*



Choice of the model (2/5)

- PROBLEM → A friend has a 750 sq ft house
  - *What price could he get for selling his house?*

- Possible approaches
  - *Linear Model*
    - *The answer is $150'000*
  - *Quadratic model*
    - *The answer is $200'000*

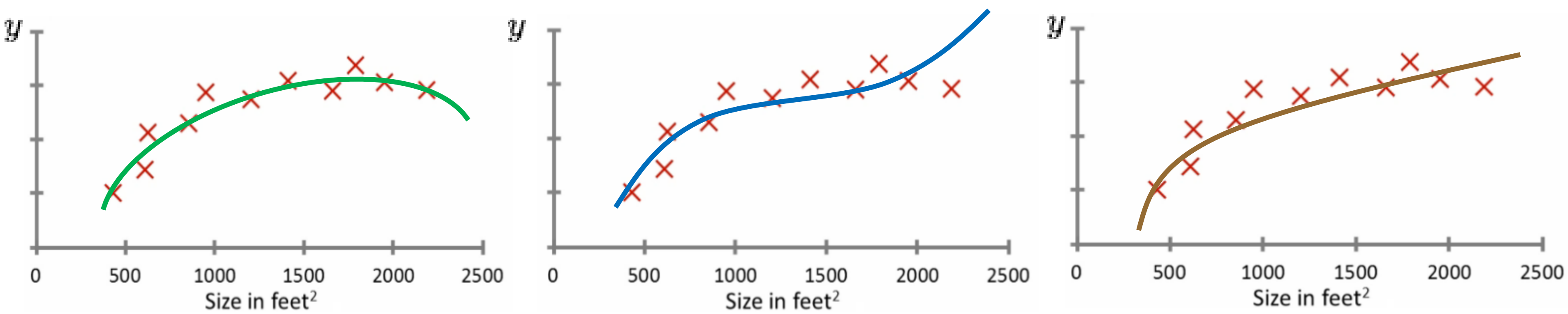


- Each is a way to perform regression
  - *We will come back to this . …*

Choice of the model (3/5)

- A priori, you can choose between different models
  - *quadratic* → *the price increases and then decreases*
  - *cubic* → *the price increases quickly*
  - *square root* → *the price increases slowly*

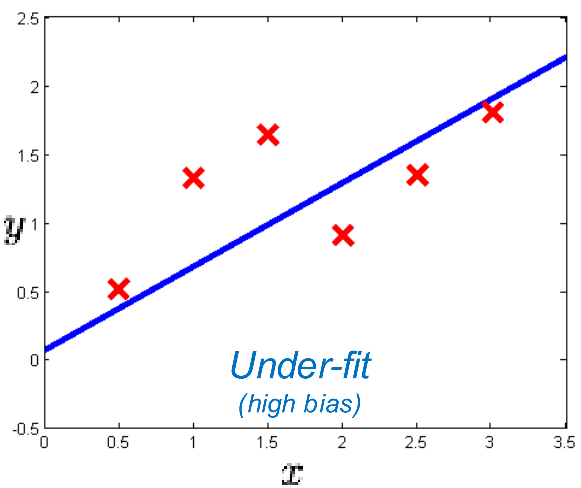
$f_\theta(x) = \theta_0 + \theta_1 x + \theta_2 x^2$ $f_\theta(x) = \theta_0 + \theta_1 x + \theta_2 x^2 + \theta_3 x^3$ $f_\theta(x) = \theta_0 + \theta_1 x + \theta_2 \sqrt{x}$



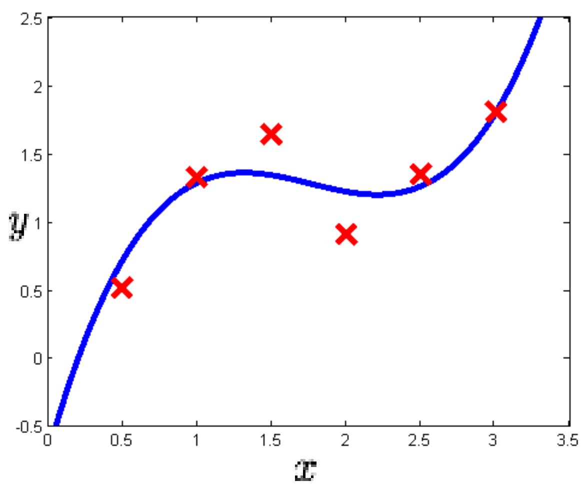
Choice of the model (4/5)

- Which model is most suitable?
  - *Under-fitting → the prediction is too far from the real responses*
  - *Over-fitting → the prediction is too close to the real responses*

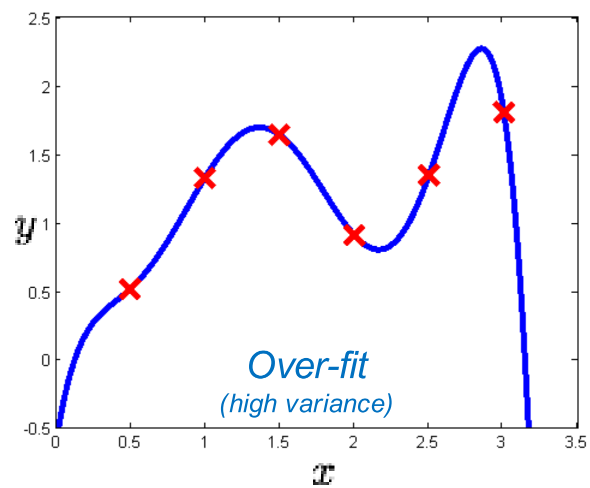
$f_\theta(x) = \theta_0 + \theta_1 x$



$f_\theta(x) = \theta_0 + \theta_1 x + \cdots + \theta_3 x^3$



$f_\theta(x) = \theta_0 + \theta_1 x + \cdots + \theta_5 x^5$



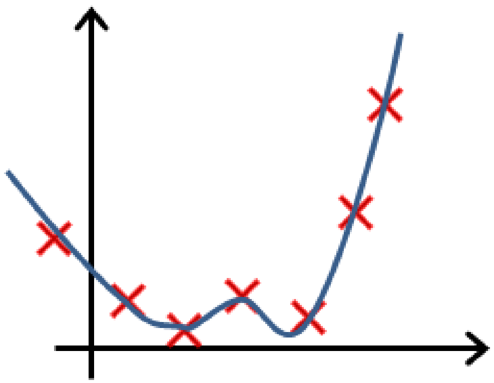
Choice of the model (5/5)

- Overfitting is **bad** and should **always** be avoided.
  - *The model predicts the training data very well...*
  - *...but it fails to predict the test data well.*
- L'over-fitting is causezd by the following factors
  - *The model is very complex (e.g., highly nonlinear)*
  - *The number of model parameters is very high*
  - *The training base is too small*

Quiz

- In which figure the model suffers from over-fitting or under-fitting?

1.



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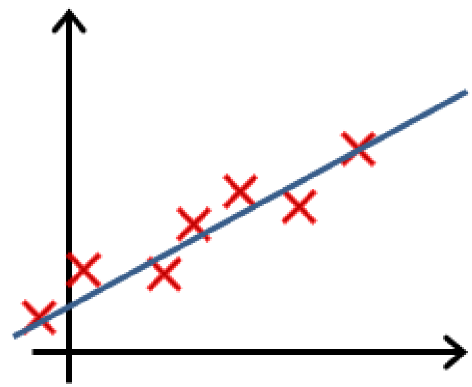

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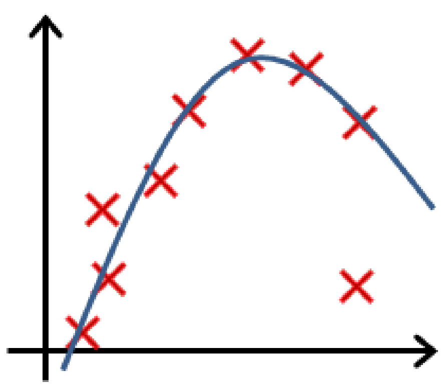

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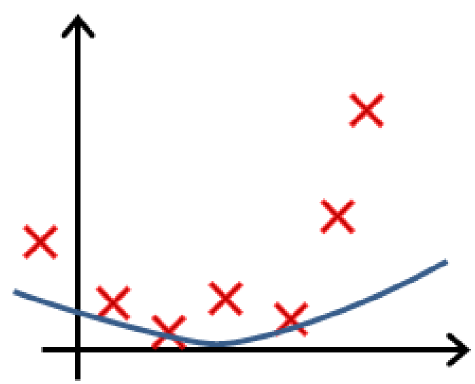
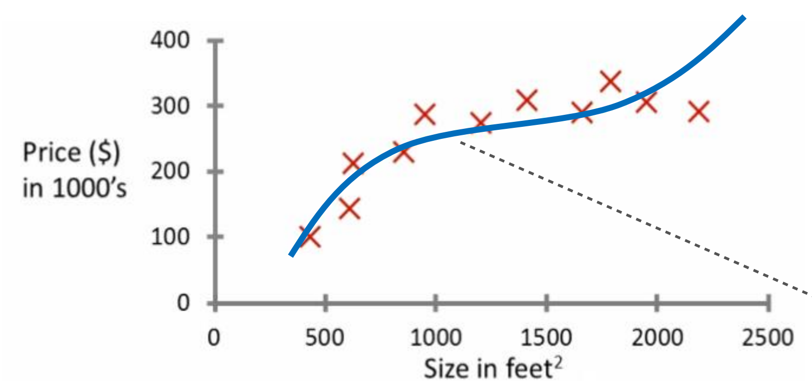
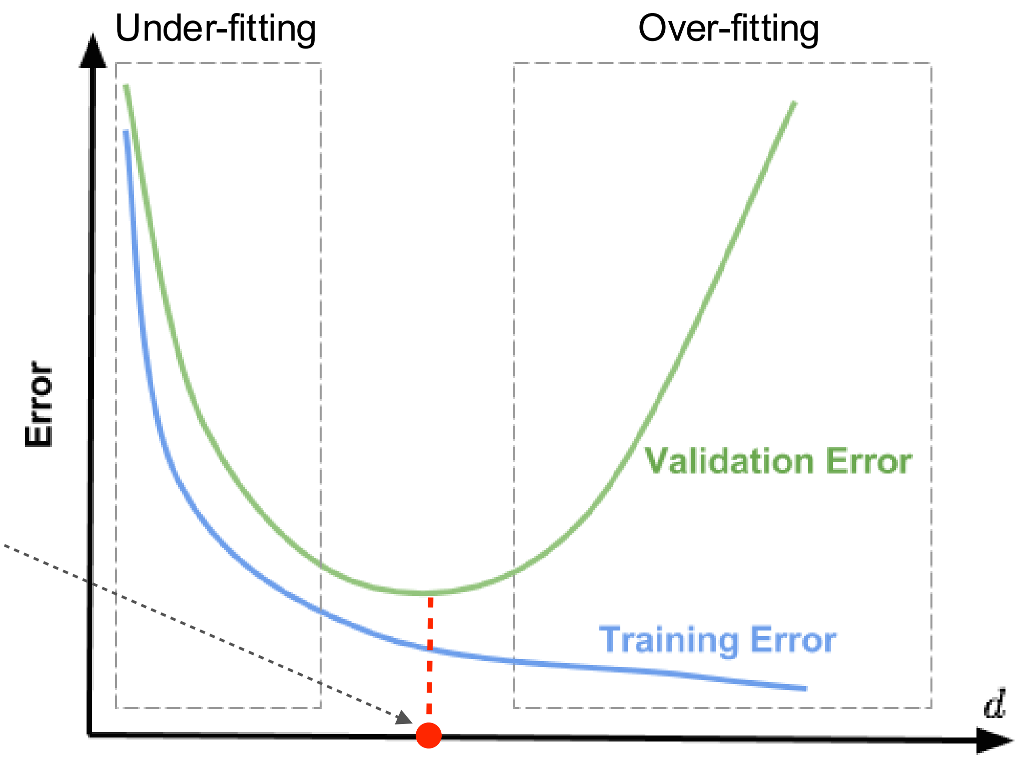


Validation (3/3)

- Example → Polynomial regression
  - *What degree of the polynomial should be chosen?*

$$f_\theta(x) = g(\theta_0 + \theta_1 x + \cdots + \theta_d x^d)$$





Quiz

- Let's say you've learned a prediction model that performs very well on the training data.
- What should we expect?

1) *The error on the training data is **low,** while the error on the test data is **high.***

2) *The error on the training data is **low**, while the error on the test data is **low**.*

3) *The error on the training data is **high**, while the error on the test data is **low**.*

4) *The error on the training data is **high**, while the error on the test data is **high**.*

SMART RETAIL: MACHINE LEARNING IN UAE'S RETAIL SECTOR

User Cases with Real Impact & Local Numbers

IN THIS PRESENTATION

Real ML/DL use cases in UAE retail

Exploring how leading retailers are implementing machine learning and deep learning to transform operations

Business metrics & customer impact

Quantifiable results and ROI from AI implementation across the retail value chain

Clear, non-technical explanations

Breaking down complex AI concepts into practical business applications for retail executives

PERSONALIZED RECOMMENDATIONS

Real-Time Personalization

Carrefour UAE's partnership with Advertima AI detects shopper demographics and behavior patterns to deliver tailored offers instantly

UAE-Wide Rollout

Technology scheduled for deployment across all UAE hypermarkets by May 2025, creating a unified personalized shopping experience

Business Impact

23%

Increase in conversion rates on personalized offers compared to standard promotions

17%

Higher average basket value when shoppers engage with AI-recommended products

41%

Improvement in customer loyalty program engagement since pilot launch

Made with GAMMA

QUICK-COMMERCE POWERED BY AI

Talabat UAE has revolutionized delivery through AI-powered logistics, with impressive 2022 results:

37%

Order Increase

Year-over-year growth in total delivery orders

70%

Non-Food Growth

Expansion in quick-commerce categories beyond restaurants

60%+

tMart Growth

Increase in Talabat's grocery delivery vertical

68%+

Cashless Payments

Digital transactions facilitated by seamless AI integration

AI algorithms optimize demand forecasting, route efficiency, and promotional targeting to achieve these results.

Made with GAMMA

AI CHATBOTS & AUTOMATED SUPPORT

Leading UAE platforms like Talabat, Noon, and Careem deploy AI chatbots to provide instant customer support 24/7, handling thousands of inquiries

76%

UAE consumers who value chatbots for simple inquiries

66%

Customers who prefer human assistance for complex issues

82%

Reduction in average wait times for customer support

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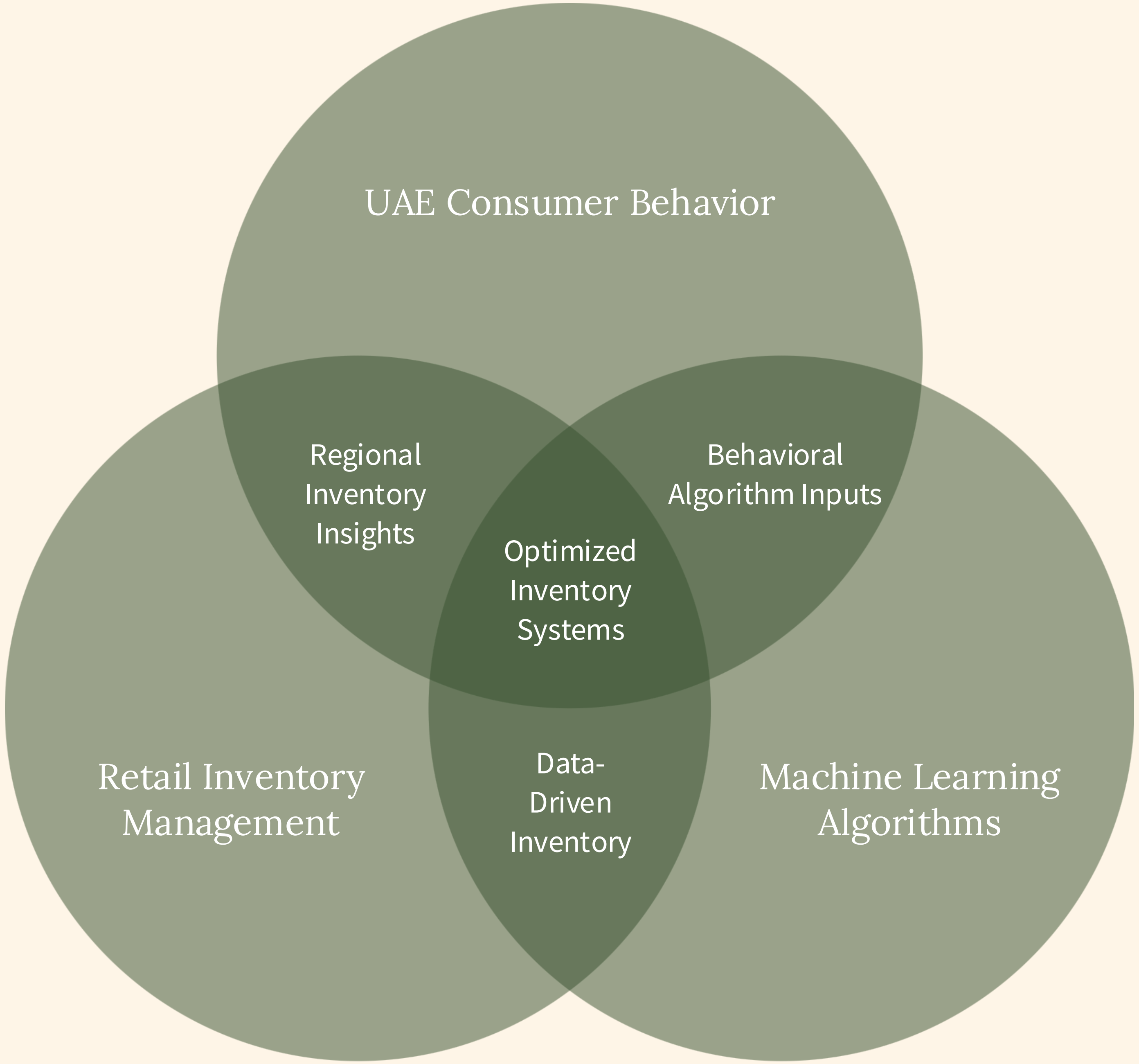
INVENTORY & SUPPLY FORECASTING



Dubai Airports Case Study

- ML algorithms analyze historical sales, seasonal trends, and flight schedules
- 30% improvement in forecast accuracy across retail outlets

Retailer Benefits

- Reduced waste in perishable goods categories
- Improved product freshness and availability

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IN-STORE ANALYTICS & LAYOUT OPTIMIZATION

Data Collection

Carrefour partners with Advertima AI to deploy advanced sensors that anonymously track shopper movement and engagement

Real-Time Analysis

Machine learning algorithms identify patterns in customer behavior, dwell time, and product interaction

Layout Optimization

Store layouts are continuously refined based on AI insights, improving product placement and customer flow

Measurable Results

Optimized layouts have increased dwell time by 14% and basket size by 9% in pilot locations

Made with GAMMA

DATA-DRIVEN PRICING & PROMOTIONS

Dynamic Pricing

- Algorithms adjust prices based on demand, inventory, competition
- 12-15% boost in sales during promotional events
- Balances profit margins with market share objectives

Smart Promotions

- AI identifies optimal product bundles and offers
- Personalized discounts based on customer value
- 20% higher redemption rates than standard promotions

Leading UAE e-commerce platforms like Noon and Talabat leverage machine learning to

Made with GAMMA

MARKET INSIGHTS & PRODUCT OPTIMIZATION

How Talabat Data Helps Brands

1. Aggregated customer preferences and ordering patterns reveal unmet market needs
2. Price sensitivity analysis helps brands optimize pricing strategies
3. Delivery performance data identifies logistics bottlenecks

Measurable Impact

25%

Average revenue growth for brands using Talabat insights

20%

Reduction in delivery complaints after logistics optimization

15%

Increase in repeat purchases through targeted offerings

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QUICK RECAP: UAE RETAIL AI LANDSCAPE

Use Case	UAE Players	Key Numbers	Business Impact
Personalization	Carrefour	Rolling out May 2025	↑ Engagement & basket size
Quick-commerce	Talabat	37% ↑ orders	↑ Speed & market reach
Chatbots	Talabat, Noon, Careem	76% value for simple inquiries	↓ Wait time & support costs
Inventory	Dubai Airports, retailers	Forecast accuracy ↑30%	↓ Waste & stockouts
In-store analytics	Carrefour	Real-time shopper detection	Optimized layouts & flows
Dynamic pricing	Noon, Talabat	12-15% sales boost	Balance volume & margins
Market insights	Talabat	Up to 25% revenue growth	Product & logistics optimization

AI adoption in UAE retail is accelerating, with both international players and local champions implementing sophisticated machine learning solutions to gain competitive advantage.

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