Applied Machine Learning for Business Analytics

Lecture 12: Why do ML Projects Fail in Business

Lecturer: Zhao Rui

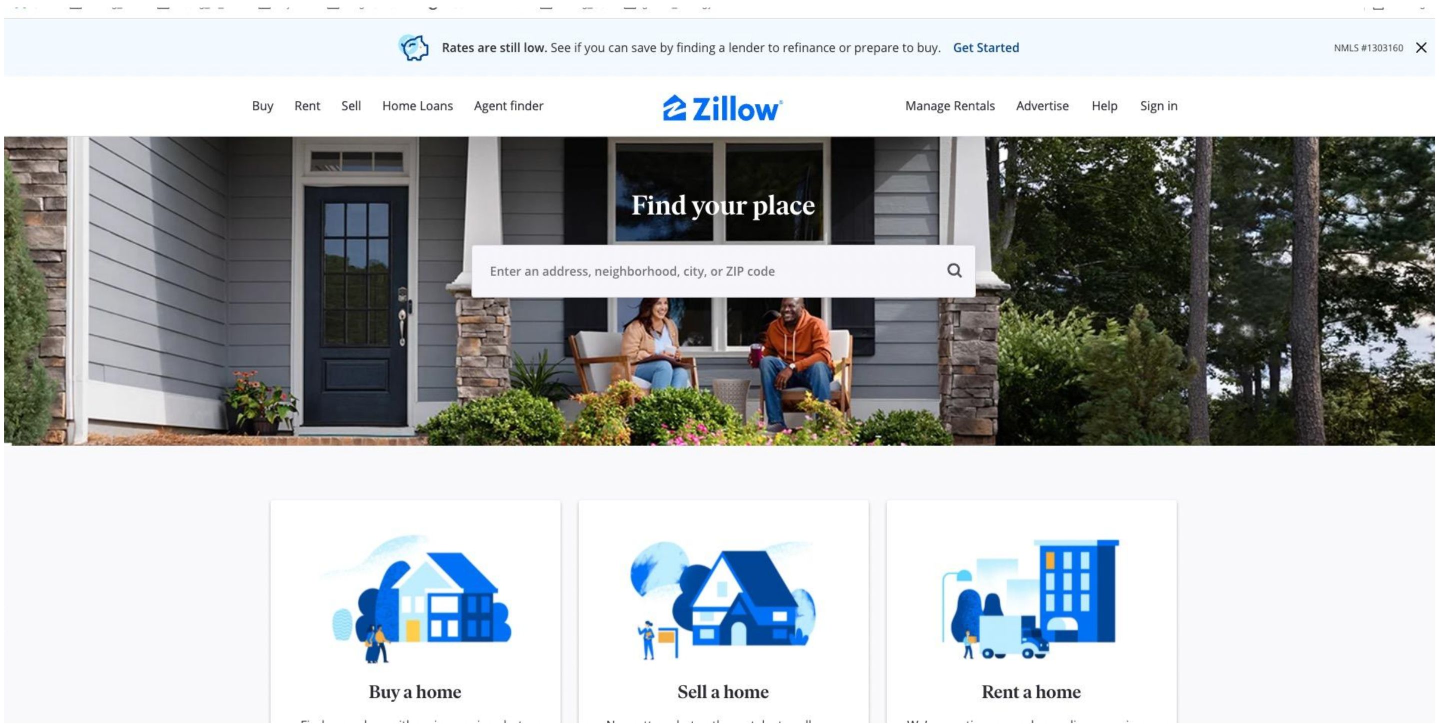
Agenda

1. Zillow Offers
2. Causes of ML Failures
3. Understanding Data Science and Analytics Roles
4. Courser Summary

1. Zillow Offers

Zillow

- an America online real-estate marketplace company



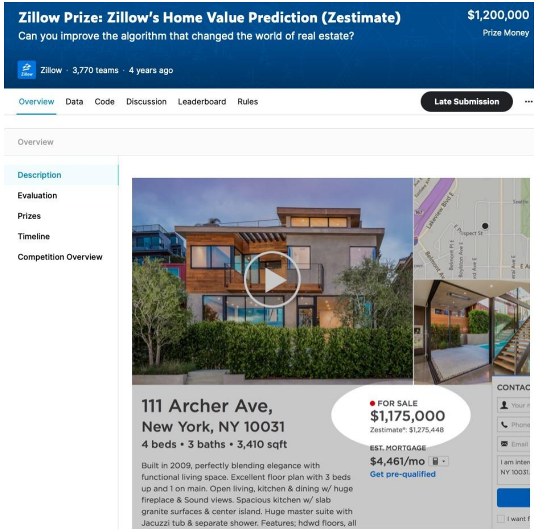
Zillow’s Business Model

- How does Zillow make money?
  - https://seoaves.com/zillow-business-model-how-does-zillow-make-money
- Zillow Offers:
  - The system called “Zestimate” will analyze multiple data and predict the housing price as the bids for the seller
  - A home sale can be completed in a matter of hours
  - Due to the speed and convenience of the sale process, zillow can purchase houses below market value. After repairs and simple renovation, the houses could be sought to a new buyer at a higher price.
  - The delta in the price + commission fees charged from buyer and seller are the gross profits

1M Kaggle Competition

- At 2018, Zestimate launched a one-million kaggle competition
- In the competition, you will build machine learning models to predict the log error between the actual sale price and the Zestimate based on all the features of a home

$$logerror = log(Zestimate) - log(SalePrice)$$



https://www.kaggle.com/c/zillow-prize-1

1M Kaggle Competition

- The winning solution pushed the Zestimate's current nationwide error rate of 4.5% to below 4%

Public Private

The private leaderboard is calculated with approximately 49% of the test data.
This competition has completed. This leaderboard reflects the final standings.

Prize Winners

#	△	Team	Members	Score	Entries	Last	Code
1	▲ 9	Zensemble		0.07408	253	4Y	
2	▲ 1	Juan Zhai 巻宅		0.07421	53	4Y	

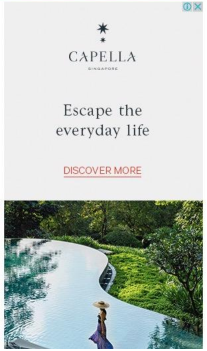
Meet the 'Zillow Prize' winners who get $1M and bragging rights for beating the Zestimate

BY KURT SCHLOSSER on January 30, 2019 at 5:00 am

Share 102 Tweet Share Reddit Email

Zillow Chief Analytics Officer Stan Humphries, left, presents a check to Nima Shahbazi, a member of the team that won the Zillow Prize. (Zillow Photo)

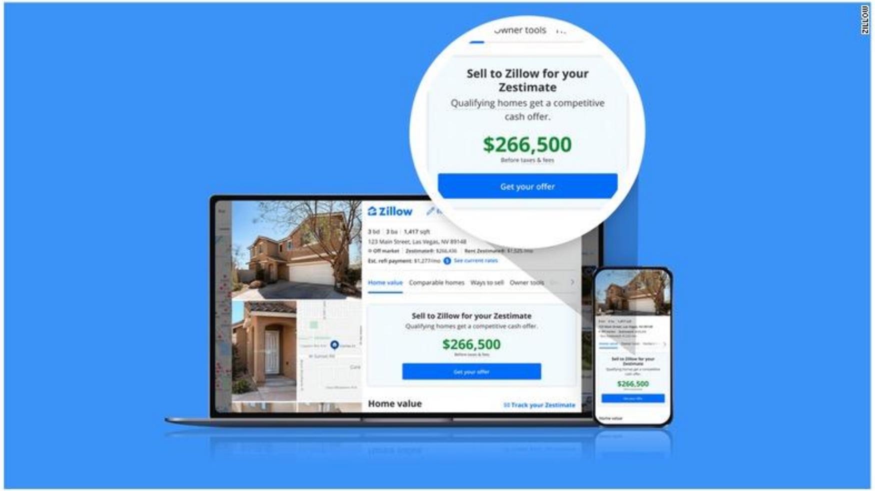
The GeekWire Awards return May 12, 2022!



Zestimates was deployed to make offers

Zillow will now make cash offers for homes based on its 'Zestimates'

By Clare Duffy, CNN Business
Updated 1550 GMT (2350 HKT) February 25, 2021



Zillow's "Zestimates" will now represent initial cash offers to homeowners in some markets.

https://edition.cnn.com/2021/02/25/tech/zillow-zestimate-cash-offer/index.html

Stock Price from Oct 2021 to Mar 2022

What went wrong with Zillow Offers?

Zillow, facing big losses, quits flipping houses and will lay off a quarter of its staff.

The real estate website had been relying on its algorithm that estimates home values to buy and resell homes. That part of its business lost about $420 million in three months.

Zillow is sitting on thousands of houses worth less than what the company paid for them. Caitlin O'Hara for The New York Times

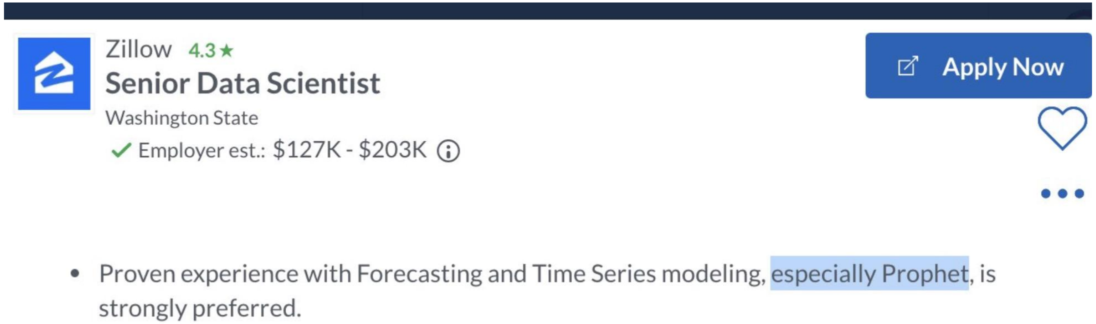
https://www.nytimes.com/2021/11/02/business/zillow-q3-earnings-home-flipping-ibuying.html

What went wrong with Zillow Offers?

1. Use ML to predict home prices
2. Use predicted prices to flip houses
3. ML models over-predict house prices
4. Buy houses at higher prices

Blaming game

1. Prophet: A python library for forecasting
2. Kaggle-style data science
3. Leadership
4. ML/DS team



More insightful discussion:
https://ryxcommar.com/2021/11/06/zillow-prophet-time-series-and-prices/

Prophet

- The model is developed by Facebook to predict the web traffic
  - Housing price do not have strong seasonality pattern which is different from web traffic

This is an accurate description of what Prophet's model is. To get a little more in the weeds, Prophet does the following linear decomposition:

- `g(t)`: Logistic or linear growth trend with optional linear splines (linear in the exponent for the logistic growth). The library calls the knots "change points."
- `s(t)`: Sine and cosine (i.e. Fourier series) for seasonal terms.
- `h(t)`: Gaussian functions (bell curves) for holiday effects (instead of dummies, to make the effect smoother).

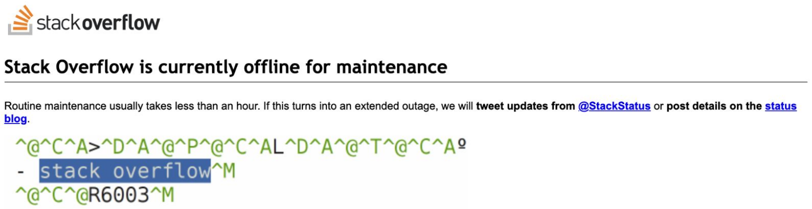
Adverse Selection

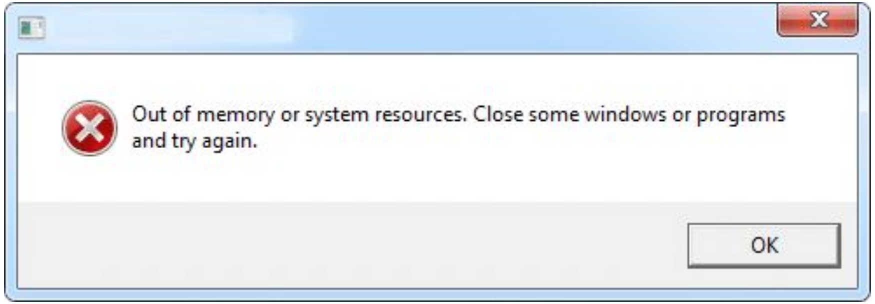
- Even the model accuracy is high, property owners will only sell when the predicted price is higher than their expected price

2. Causes of ML Failures

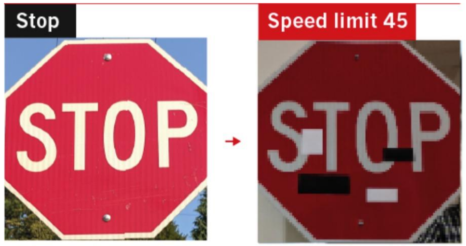
ML systems fail silently

Normal softwares fail





ML systems fail



Amazon scraps secret AI recruiting tool that showed bias against women

That is because Amazon's computer models were trained to vet applicants by observing patterns in resumes submitted to the company over a 10-year period. Most came from men, a reflection of male dominance across the tech industry.

In effect, Amazon's system taught itself that male candidates were preferable. It penalized resumes that included the word "women's," as in "women's chess club captain." And it downgraded graduates of two all-women's colleges, according to people familiar with the matter. They did not specify the names of the schools.

Amazon scraps secret AI recruiting tool that showed bias against women (Reuters, 2018)

Japan’s Henn na Hotel fires half its robot workforce

“Guests complained their robot room assistants thought snoring sounds were commands and would wake them up repeatedly during the night.”

https://www.hotelmanagement.net/tech/japan-s-henn-na-hotel-fires-half-its-robot-workforce

What is an ML failure?

A failure happens when one or more expectations of the system is violated.

Two types of expectations:

- Operational metrics: e.g. response time, downtime
- ML metrics: e.g. accuracy, MSE, BLUE score (machine translation)

What is an ML failure?

A failure happens when one or more expectations of the system is violated

- Traditional software: mostly operational metrics
- ML systems: operational + ML metrics
    - Ops: returns the risk scores of users within 800ms latency on average
    - ML: Accuracy as 80%

ML system failures

- If you call API to infer the user's risk score and get no response-> ops failure
- If the prediction is incorrect -> ML failure?

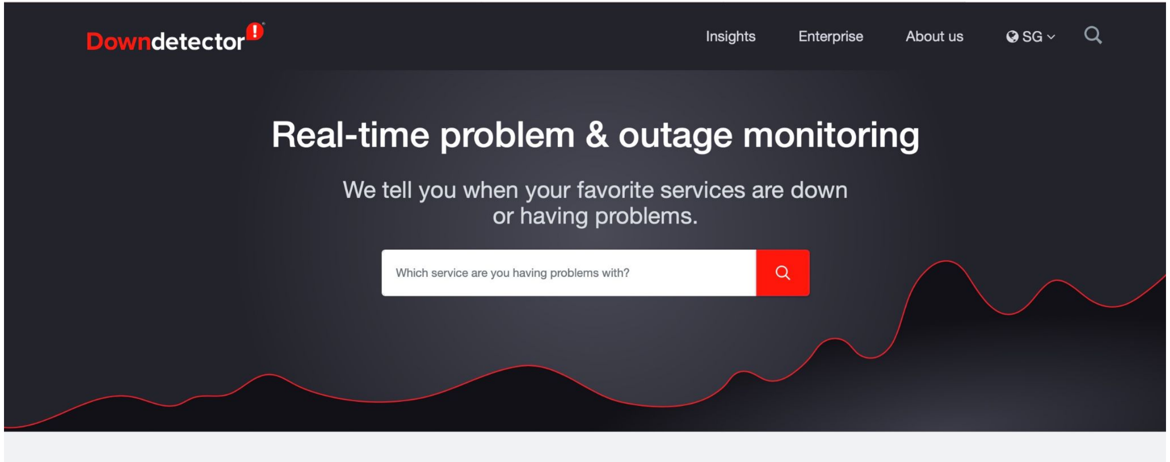
ML system failures

- If you call API to infer the user's risk score and get no response-> ops failure
- If the prediction is incorrect -> Might not be

ML failure when the predictions are consistently wrong

What are Ops Failures

- They are normal software systems' failures:
  - Network issues: downtime / crash
  - Deployment issues
  - Hardware issues
  - Dependencies issues



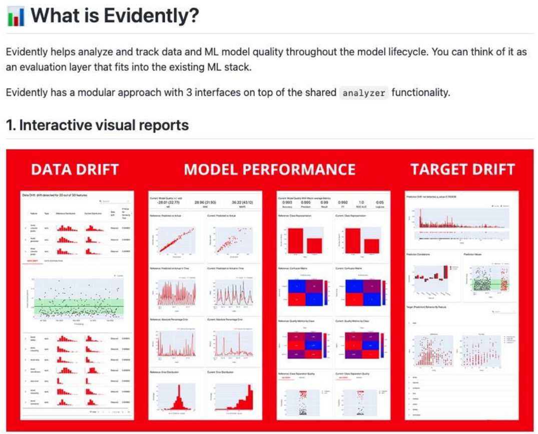
ML-specific failures (during/post deployment)

1. Production data differing from training data
2. Degenerate feedback loops

What are the potential issues for the pre-deployment stage?

Production data differing from training data

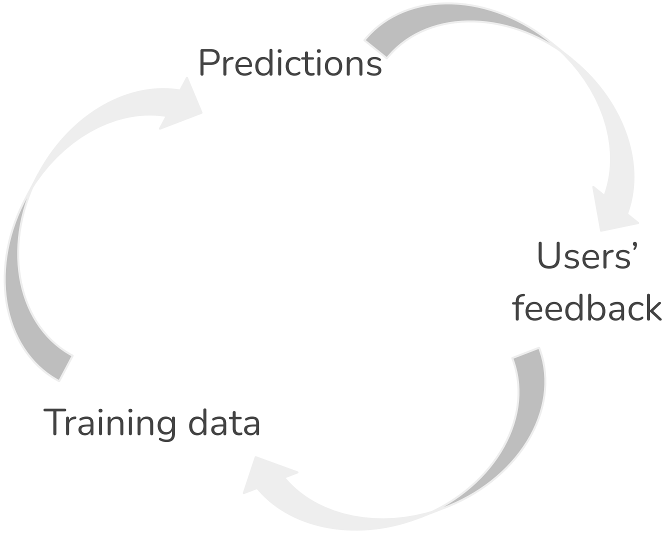
- Train-serving skew:
  - Model performing well during development but poorly after production
- Data distribution shifts
  - Model performing well when first deployed, but poorly over time



https://github.com/evidentlyai/evidently

Degenerate feedback loops

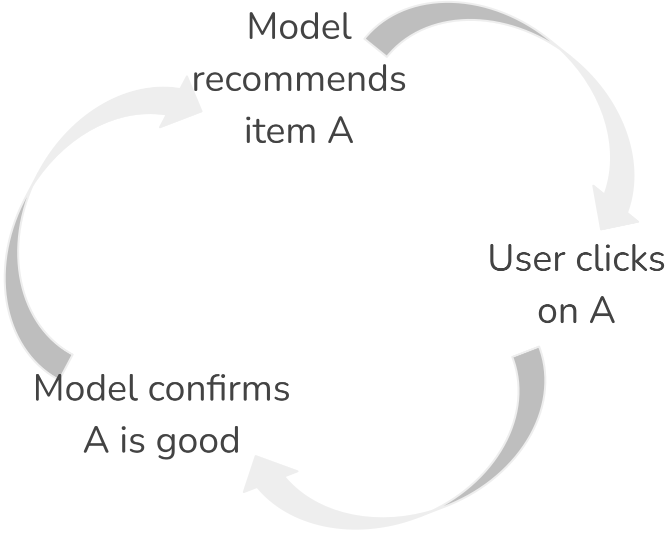
- When predictions influence the feedback, which is then used to extract labels to train the next iteration of the model
- Common in tasks with natural labels



It is not only dangerous for the business, but also for society

Degenerate feedback loops: recsys

- Originally, A is ranked marginally higher than B -> model recommends A
- After a while, A is ranked much higher than B



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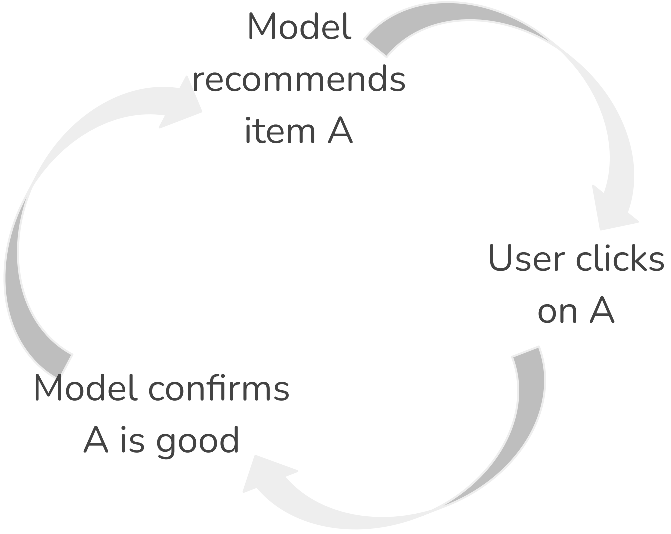

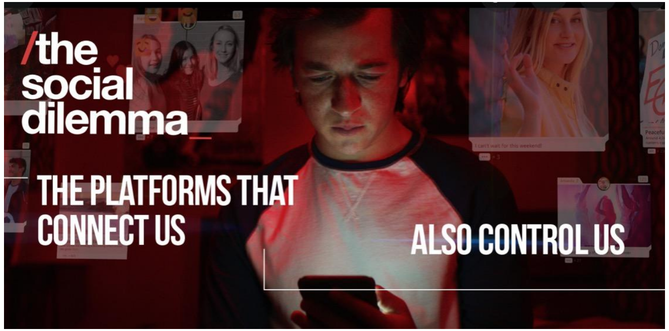

Degenerate feedback loops: resume screening

- Originally, model thinks X is a good feature
- Model only picks resumes with X
- Hiring managers only see resumes with X, so only people with X are hired
- Model confirms that X is good

Replace X with:

- Has a name that is typically used for gender A
- Went to NUS, MSBA

Degenerate feedback loops: resume screening

- Originally, model thinks X is a good feature
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- Hiring managers only see resumes with X, so only people with X are hired
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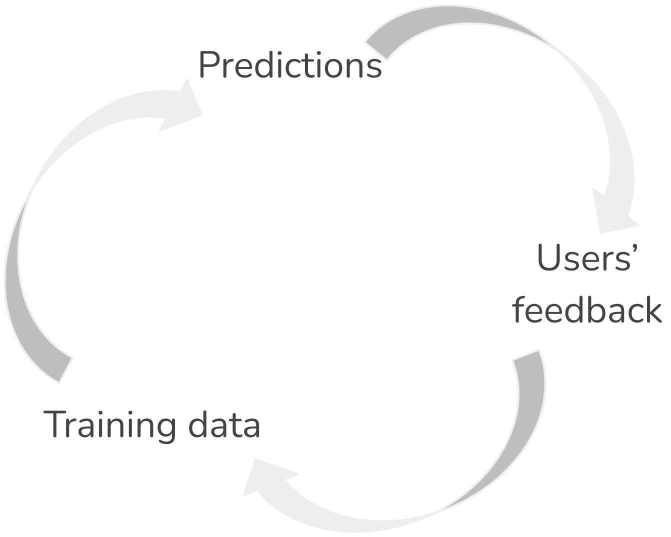
Tracking feature importance might help!

Detecting degenerate feedback loops

Only arise once models are in production -> hard to detect during training



Well studied in Recommendation System

Degenerate feedback loops: mitigate

1. Randomization
2. Positional features

Degenerate Feedback Loops in Recommender Systems

Ray Jiang, Silvia Chiappa, Tor Lattimore, András György, Pushmeet Kohli
{rayjiang,csilvia,lattimore,agyorgy,pushmeet}@google.com
DeepMind London, UK

https://arxiv.org/abs/1902.10730

3. Understanding Data Science and Analytics Role

Data-Driven Decision

- Understand your business problem
- Identify key challenges and hypothesis in the business problem
- Use data analytics and science methodologies to **test** the hypothesis and **solve** the challenges

How can we make impacts?

- Four stages:
  - How to track/log data?
    - To solve the biz problem, which kind of informations/data are required? -> design trackers
    - It all comes from your business understanding
    - We might need to talk with tech team to design the robust mechanism to make sure the data collection is correct

How can we make impacts?

- Four stages:
    - How to track/log data?
    - How to process data?
        - data cleaning
        - data quality check
        - schema design
        - DE might help to design the raw tables from multiple sources of logs while DSA team needs to design intermedia tables or data mart.

How can we make impacts?

- Four stages:
  - How to track/log data?
  - How to process data?
  - How to analyze data?
    - Dashboard
    - Attribution
    - Metrics design
    - Experimentation
    - Modeling (Data Scientist)

Myth: Modeling is more advanced or DS is on top of DA.

How can we make impacts?

- Four stages:
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    - Modeling (Data Scientist)

Problem Formulation First, Less Methodology-focused

Simple Tool to solve important problem > Complex tool to solve important problem >> Solve trivial problem

How can we make impacts?

- Four stages:
  - How to track/log data?
  - How to process data?
  - How to analyze data?
  - How to automate the decision-making process?
    - Machine learning is the answer (rule-based system, supervised models and unsupervised models): data -> pattern -> decision

Toy Example

- E-commerce A: CAC in Google Ads per surface enter is 0.01 sgd and the trx conversion rate is 0.1%

Toy Example

- E-commerce A: CAC in Google Ads per surface enter is 0.01 sgd and the trx conversion rate is 0.1%
- Basic Analysis:
  - Marketing cost per transaction: 10 SGD
  - Compare the number across channels

Toy Example

- E-commerce A: CAC in Google Ads per surface enter is 0.01 sgd and the trx conversion rate is 0.1%
- Advanced Analysis:
  - Cohort analysis: after the first transaction, how many transactions would happen in the following?
  - Product Sense:
    - Another competitor: CAC is 0.1 sgd while the conversion rate is 5%
  - Funnel Analysis
  - A/B Testing
  - User Survey
  - Better Data
    - Users Income
    - Users Demographics Data
    - Other alternative data to support your hypothesis

Advanced analysis is targeted at improving the conversion rate

Open Discussion

- Steve Jobs introduced iphone in 2007
  - It is an art
  - No data support
  - Business context/understanding is the key here
- Classify dog vs Cat
  - It is a science and engineering problem
  - Fit CNN using our training data
  - Deploy the model
- Data Science is art, science and engineering problem

High-impact data science =

Business context (aka art) +

Experimentation/Modeling (aka science) +

Implementation (aka engineering)

4. Course Summary

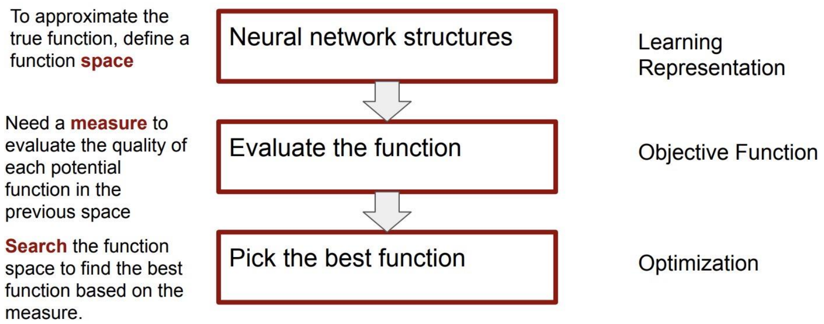
Recap: Bridge the Gap

- Introduction to Machine Learning and its **Application**
  - Gap between theory and practice
- Machine Learning **Practices**
  - Prevent potential issues before model deployment
- **Explainable** Machine Learning
  - Interpretability (remember the case: pokemon vs digimon or jpeg vs png)
- Model **Evaluation** in Machine Learning
  - Modeling
- Model **Deployment** in Machine Learning
  - Production
- Why do ML Projects **Fails** in Business
  - Business Understanding/Product Sense First

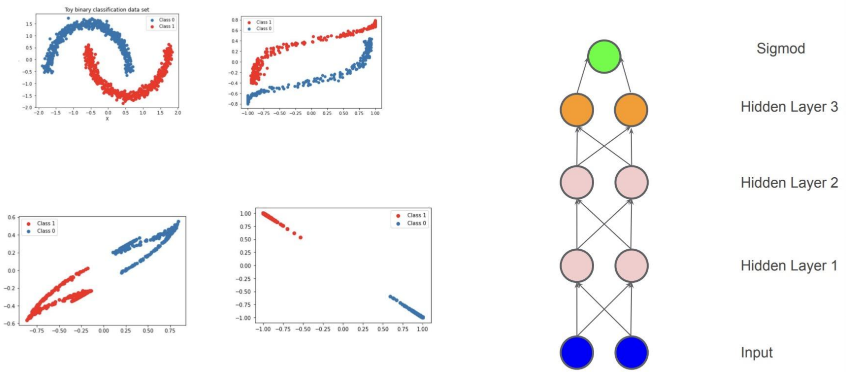
Recap: DL

- Neural Networks and Deep Learning
- Deep Learning Practices
- Auto-encoders
- Convolutional Neural Networks
- Frontiers in NLP
  - **Self-supervised** Training

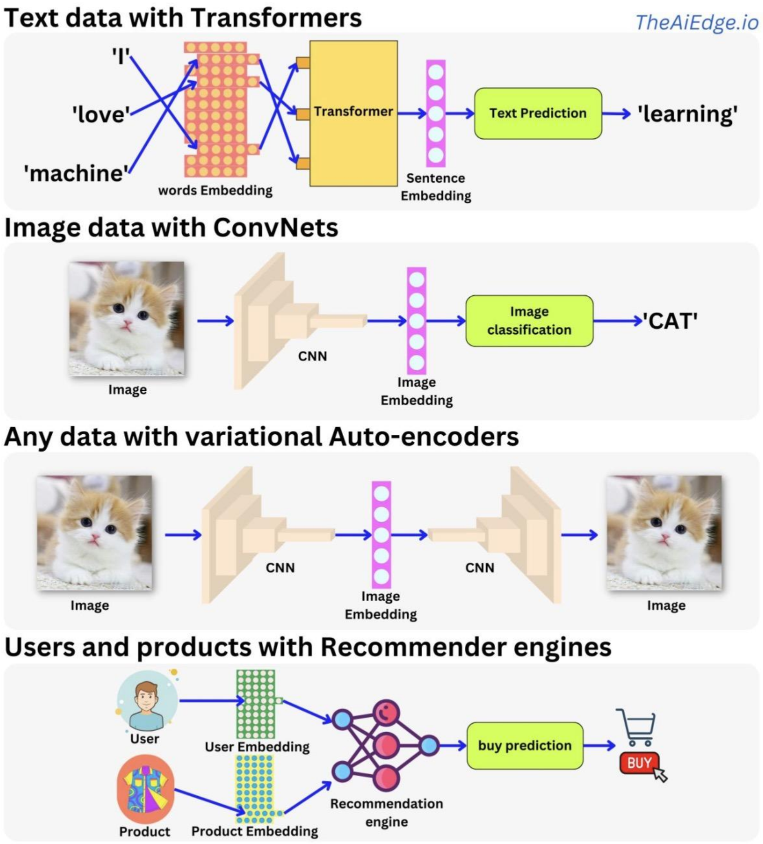
Three Steps in Deep Learning



Fully-Connected Neural Network



Recap: Embedding is everything for DL



source: https://newsletter.theaiedge.io/

Recap: Data-driven Decision

- Causal Inference for **Decision** Making
  - Data -> Insights -> Decisions
  - Without decisions, data and Insights are both cheap
  - As a data analyst or data scientist, we need to make Impact, Impact, Impact
    - Identify product-market fit
    - Improve strategies
    - Find directions
    - Fix issues
    - Quantify targets
    - Prioritization

Machine Learning is not ONLY model tuning

CONCLUSIONS

- Model-blind approaches to AI impose intrinsic limitations on the cognitive tasks that they can perform.
- The seven tasks described, exemplify what can be done with models that cannot be done without, regardless how big the data.
- DATA SCIENCE is only as much of a science as it facilitates the interpretation of data -- a two-body problem involving both data and reality.
- DATA SCIENCE lacking a model of reality may be statistics but hardly a science.
- Human-level AI cannot emerge from model-blind learning machines.

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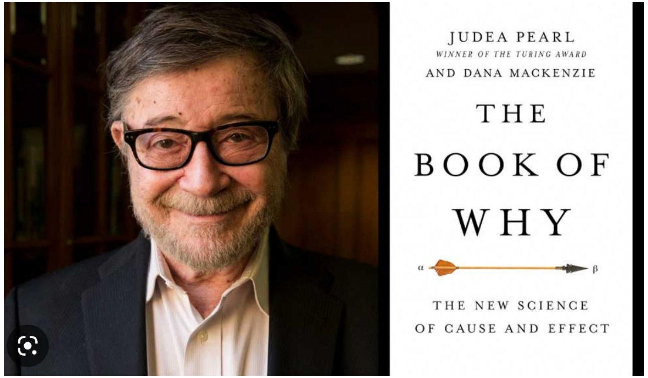

Judea Pearl

source of the slides:
http://causality.cs.ucla.edu/blog/wp-content/uploads/2017/12/nips-dec2017-bw.pdf

Frustrations of the data scientist

Here's why so many data scientists are leaving their jobs

Frustrations of the data scientist!

So to be an effective data scientist in industry it doesn't suffice just to do well in Kaggle competitions and complete some online courses. It (un)fortunately (depending on which way you look at it) involves understanding how hierarchies and politics works in business. Finding a company that is aligned with your critical path should be a key goal when searching for a data science job that will satisfy your needs. However, you may still need to readjust your expectations of what to expect from a data science role.

Source: https://towardsdatascience.com/why-so-many-data-scientists-are-leaving-their-jobs-a1f0329d7ea4