

**Siam Innovation District**

# DESIGN THINKING FOR BUSINESS INNOVATION

IDEATE

EMPATHIZE

DEFINE

PROTOTYPE

Kaweeuwut Temphuwapat  
Team Lead, Innovation Lab and CVC,  
PTT Group Design Leader,  
MBA, Stanford University d.leader, Stanford d.school

Apply Now – Aug 31, 2017 : Open for Public

Course : SEP 9 – OCT 7, Every Saturday, 09.00 - 12.00  
Room Rajakumari 60 Building (Chamchuri 10 Bldg), Fl 4  
Selected seats! Selected candidates will be fully-funded towards the course fee, worth 35,000 baht

CONTACT US

093-725-0808  
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cu.innovationhub@gmail.com

**CU INNOVATION HUB**

ION

**MACHINE LEARNING**

**Siam Innovation District Tech Talent**

**Machine Learning**

- Essential tools and libraries: Python, Jupyter Notebook, NumPy, Pandas, SciPy, Scikit-Learn, Matplotlib, and Seaborn
- Data collection through API and web scraping
- Machine Learning Algorithms reviews

Warodom Khamphanchai, Ph.D.  
Bangkok AI Ambassador,  
Ex-Software Developer at  
Samsung SmartThings in Palo Alto,  
CA. Ex-Full Stack Developer at

Sorawit Saengkyongam  
Data Scientist at Agoda,  
Google Developer Expert in  
Machine Learning.

Agenda ครับ -----

1. Meet guest developers from Silicon Valley
2. What you need to know to convince your prospective CTO or developer?
3. How can you communicate your ideas to your CTO or developer?

**24 Steps to Successful Startup Course**

I want to make happen? Join this comprehensive startup course to take your startup idea from idea to product in 6-weeks!

Tareef Jaffer  
Ex-teaching staff at MIT,  
Ex-Goolger, Serial Entrepreneur

MARTIN TRUST CENTER FOR MIT ENTREPRENEURSHIP

http://bit.ly/cueDE



# Warodom Khamphanchai, PhD

- LEAD SMART HOME/BUILDING PLATFORM DEVELOPER @ PEA
- EX-SOFTWARE DEVELOPMENT ENGINEER @ SAMSUNG SMARTTHINGS

Interests: Home/Building Automation, Internet of Things, Smart Grid, Multi-Agent systems, Data Analytics, Machine Learning, Deep Learning, AI, Energy Audit, and Technology Entrepreneurship.

## Education:

- [2011-2016] Ph.D. in Electrical and Computer Engineering,  
Virginia Tech

Dissertation: An Agent-based Platform for Demand Response Implementation in Smart Buildings

- [2009-2011] M.E. in Energy (Area of Specialization: Electric Power System Management), Asian Institute of Technology  
Thesis: A Multi-Agent Based Power System Restoration

## Approach in Distributed Smart Grid

- [2005-2009] B.E. in Electrical Engineering, Chulalongkorn University



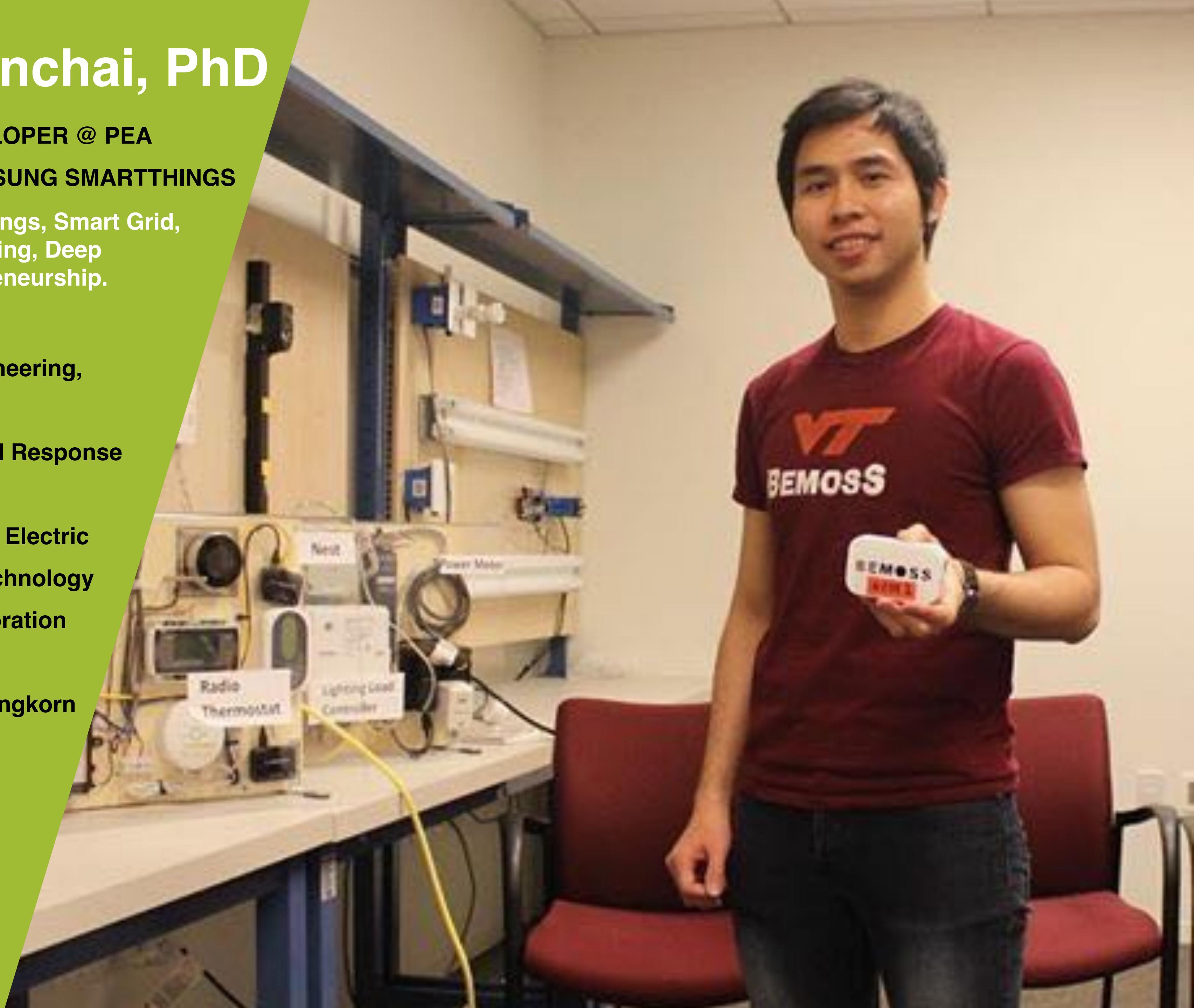
Line: kwarodom

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Email: [kwardom@vt.edu](mailto:kwardom@vt.edu)

Tel: +6695-161-5011 Github: kwarodom



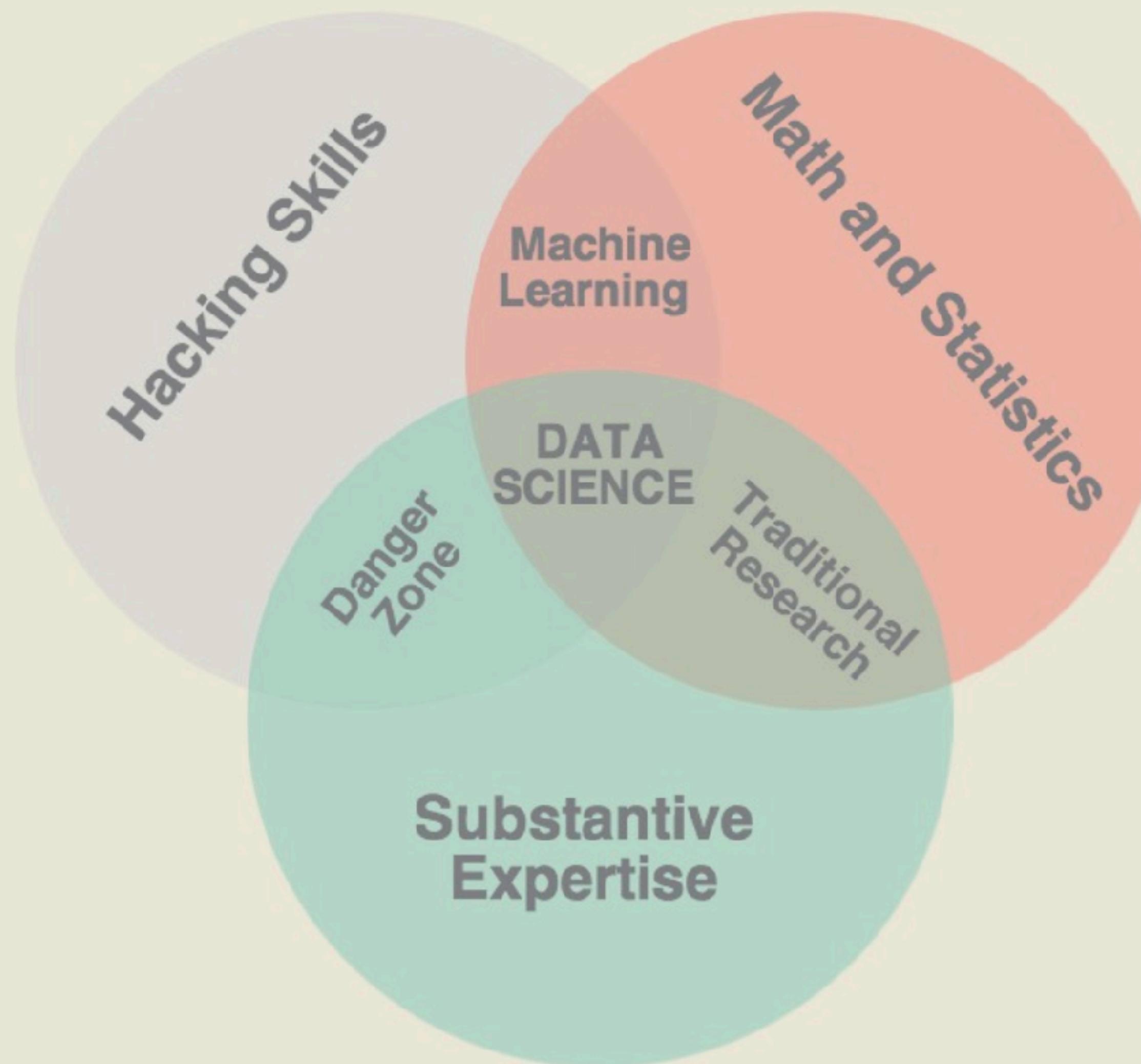


## Profile

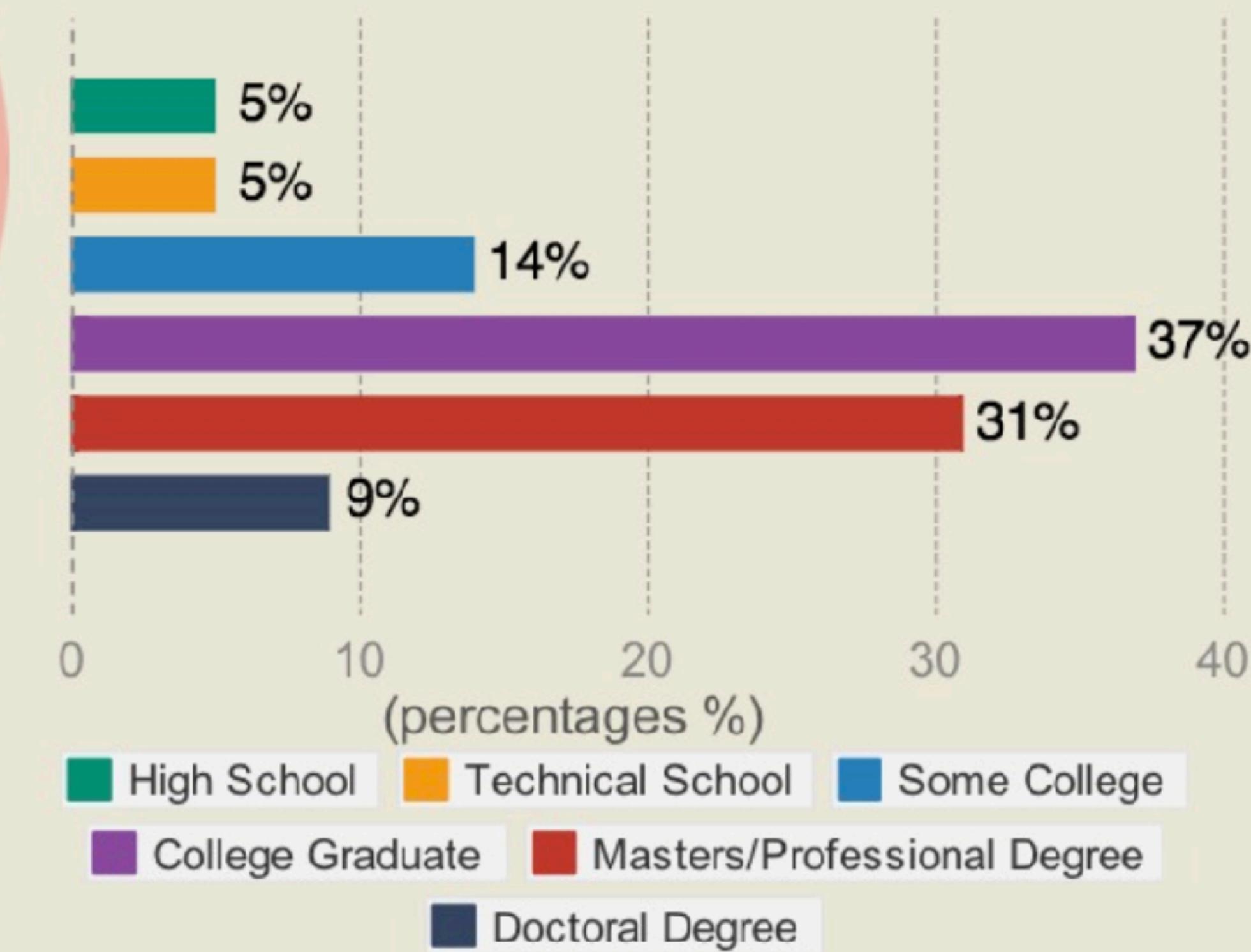
**Sorawit Saengkyongam (James)**

- Data Scientist at Agoda where he works on research and development of personalization algorithms and recommendation systems
- Google Developer Expert in Machine Learning.
- Organize Bangkok Machine Learning Meetup
- Graduated with a major in Mathematical Statistics from Chulalongkorn University (with first class honours)

# What's a data scientist?



Typical Background



A data scientist is someone who is better at statistics than any software engineer and better at software engineering than any statistician.

Gareth James  
Daniela Witten  
Trevor Hastie  
Robert Tibshirani

# An Introduction to Statistical Learning

with Applications in R



## □ Programming

- R programming language
- Python programming language
- Spreadsheet tools (like Excel)
- JavaScript and HTML
- C/C++

## □ Statistics

- Descriptive and Inferential statistics
- Experimental design

## □ Mathematics

- College Algebra
- Functions and Graphing
- Multivariable Calculus
- Linear Algebra

## □ Machine Learning

- Supervised Learning
- Unsupervised Learning
- Reinforcement Learning

## □ Data Wrangling

- Python
- Database Systems
- SQL

## □ Communication and Data Visualization

- Visual Encoding
- Data Presentation
- Knowing Your Audience

## □ Data Intuition (Thinking like a data scientist)

- Project Management
- Industry Knowledge

05

07

09

10

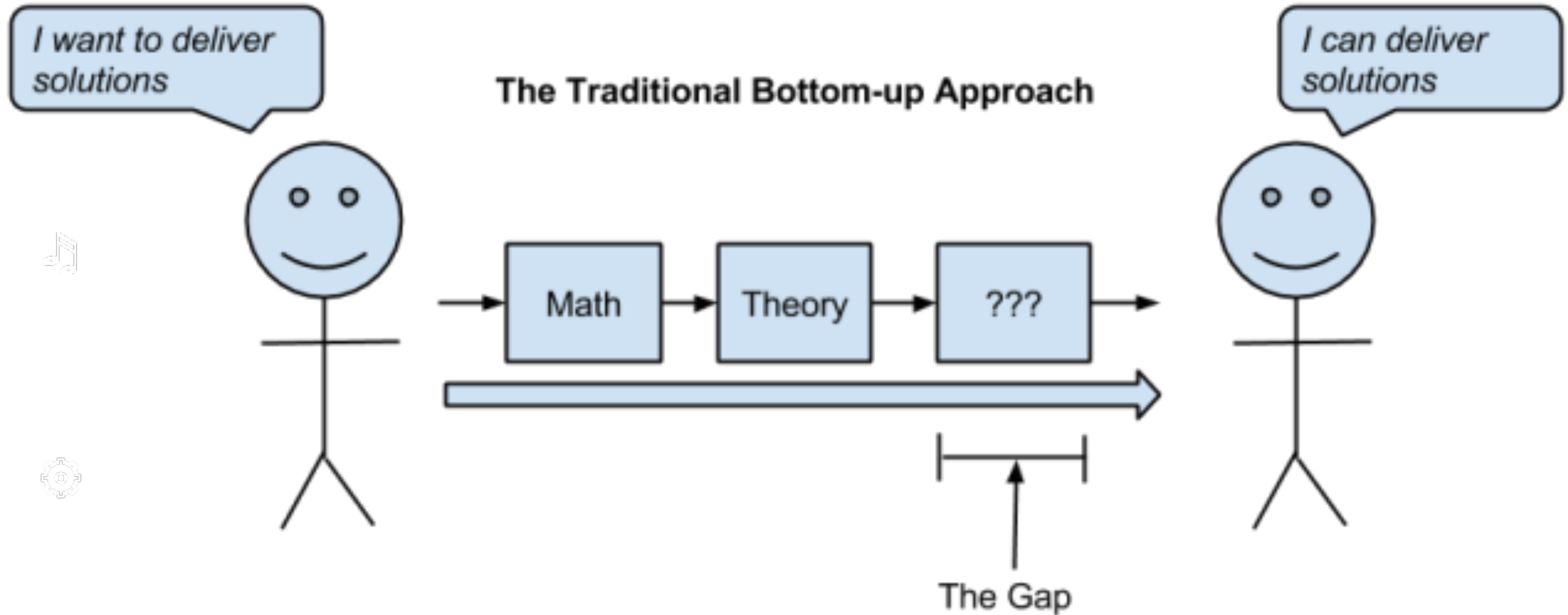
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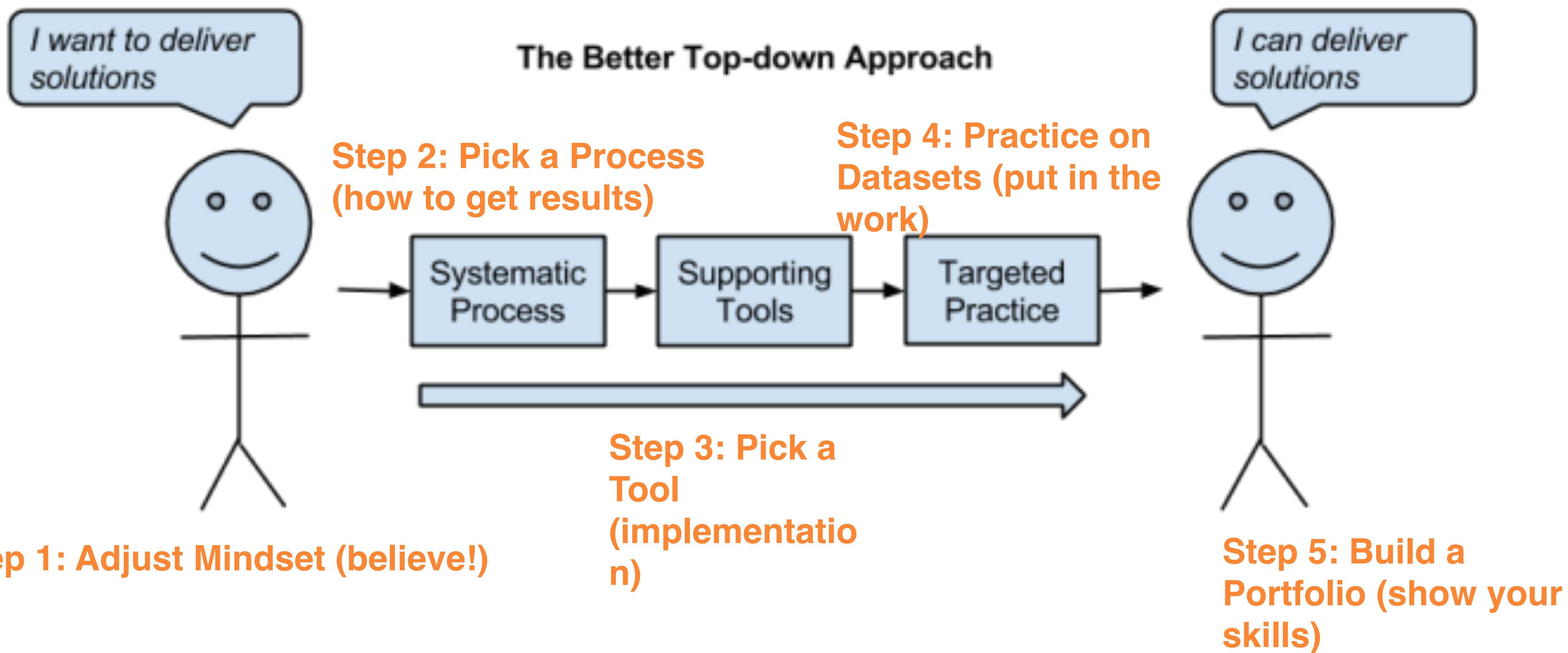
# MACHINE LEARNING PRACTITIONER





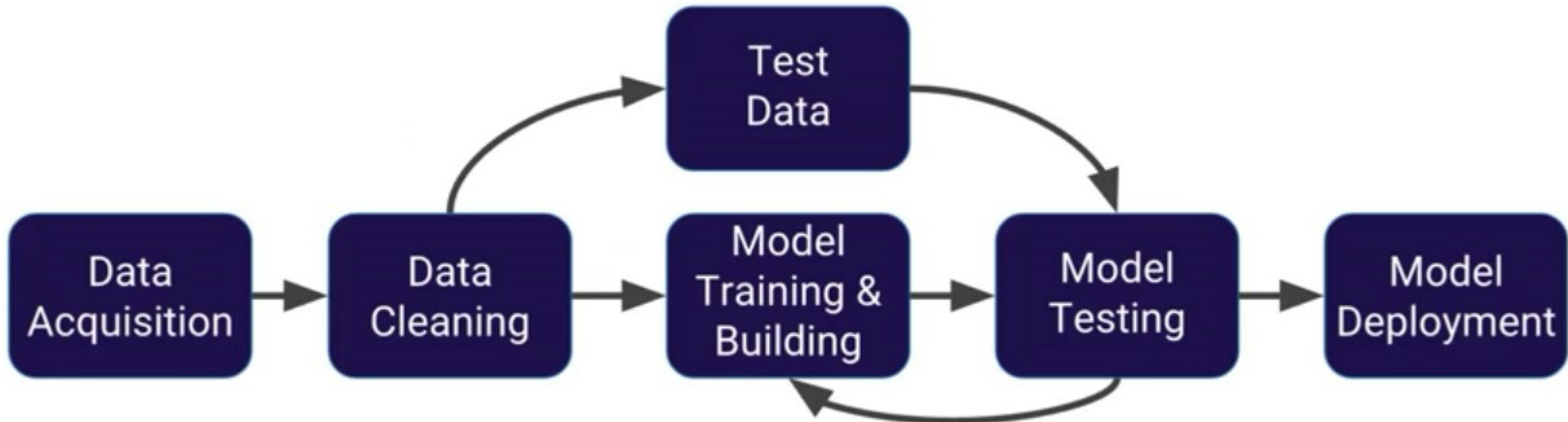
# MACHINE LEARNING PRACTITIONER

## 5-Steps To Get Started and Get Good at Machine Learning



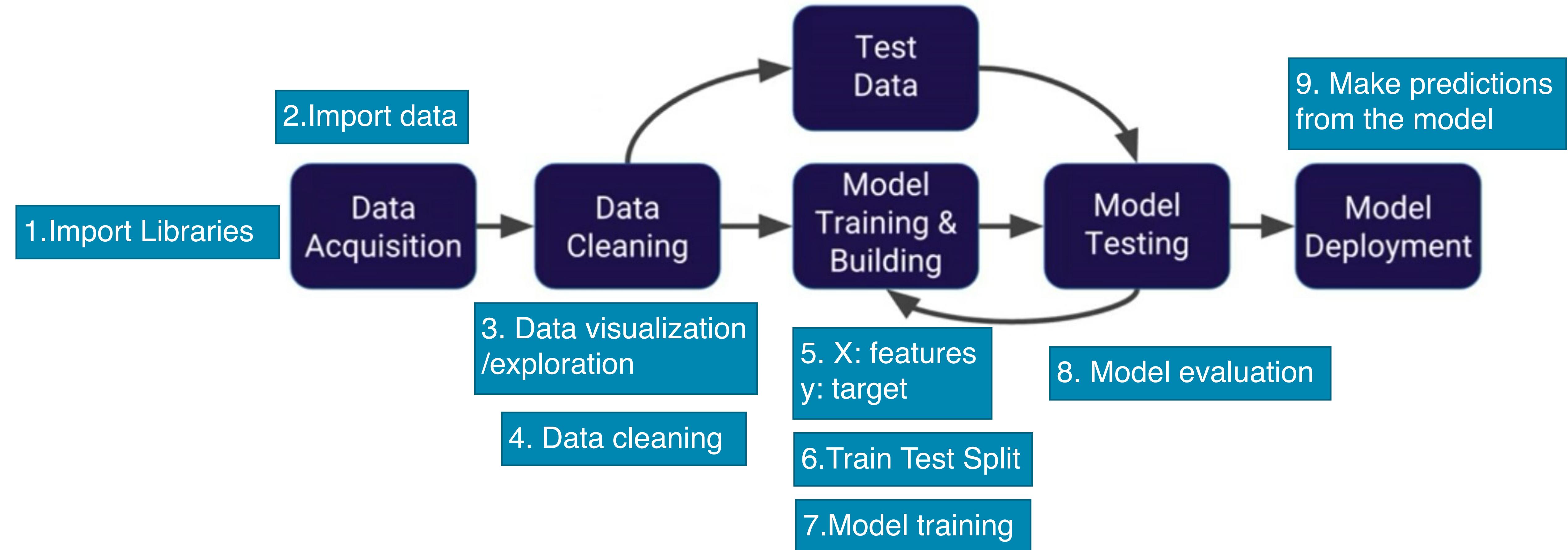


# MACHINE LEARNING PROCESS





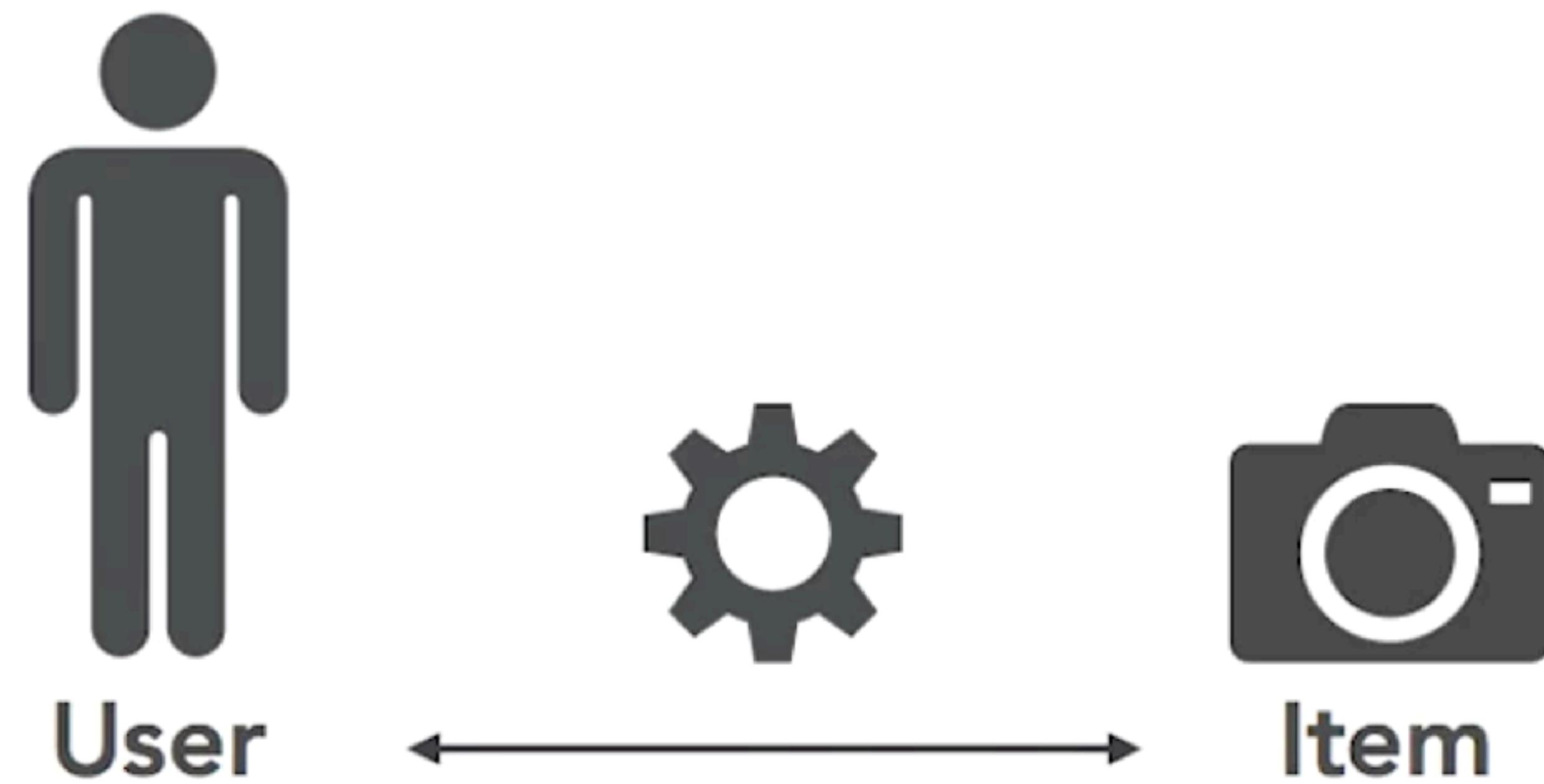
# MACHINE LEARNING PROCESS





# Introduction to Python Recommendation System

Purpose: to find and recommend items that a user is most likely to be interested in





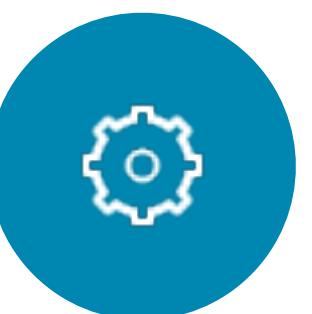
# Introduction to Python Recommendation System

1. Popularity-Based Recommender Systems
2. Correlation-Based Recommender Systems
3. Classification-Based Collaborative Filtering
4. Model-Based Collaborative Filtering
5. Content-Based Recommender Systems
- 6.



# Examples of Recommendation Engines

- Product recommendations: Amazon and Etsy
- Movie recommendation: Netflix
- Music recommendation: Apple Music
- Social connection recommendations: Facebook, LinkedIn, and Instagram



# Collaborative Filtering Systems

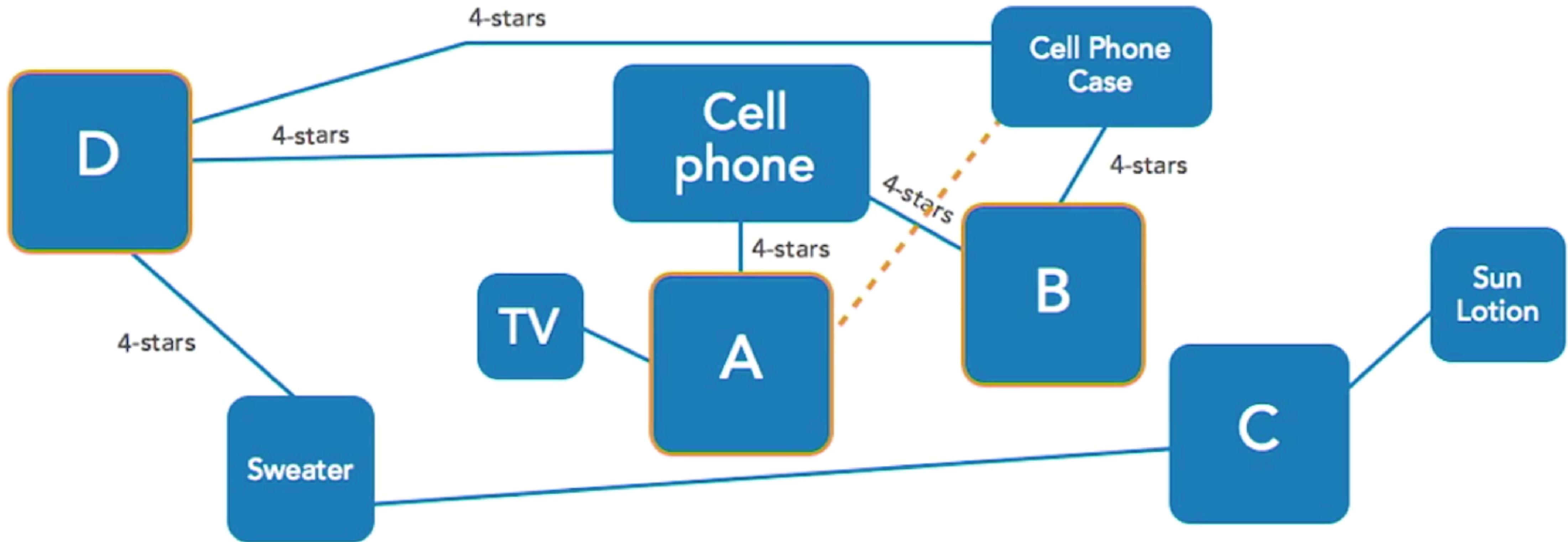
**Collaborative filtering systems recommend items based on crowdsourced information about users' preferences for items.**

**Two approaches:**

- User based
- Item based



# Conceptualizing Item-Based Filtering



User B and User D both gave high ratings to the cell phone and the cell phone case. Since User A also likes the cell phone, let's recommend to her the cell phone case also.



# Conceptualizing User-Based System

User	Age	Net Worth (\$)	Marital Status
User A	32	25,000	Divorced
User B	64	250,000	Married
User C	19	3,000	Single
User D	71	135,000	Married



Based on known user attributes, we know that User B is similar to User D. User D really likes his life insurance policy, so let's recommend it to User B also.



# Content-Based Recommender System

Content-based recommenders recommend items based on similarities between features.

City Name	Average Temperature (F) in Winter	Average Cost of Living (\$)	Average Wi-Fi Speed (MBPS)
Austin, Texas	65.1	2,147	165
Spokane, Washington	51.8	3,059	40
Miami, Florida	67	2,520	125

A user who loves Miami might also love Austin, based on the similarities between the temperature, cost of living, and Wi-Fi speeds at both places.



# Popularity-Based Recommender Systems

Based on simple count statistics

User	Place	Rating
User A	Place 1	10
User B	Place 1	8
User C	Place 2	8
User D	Place 2	7
User E	Place 1	8
User F	Place 1	7
User G	Place 1	10



Place	Rating Count
Place 1	5
Place 2	2



# Popularity-Based Recommender Systems



- Rely on purchase history data
- Are often used by online news site like Bloomberg
- Cannot produce personalized results

More popular



# Correlation-Based Recommendation Systems

- Use Pearson's  $r$  correlation to recommend an item that is most similar to the item a user has already chosen
- Item-based similarity: How correlated are two items based on user ratings?



# Correlation-Based Recommendation Systems

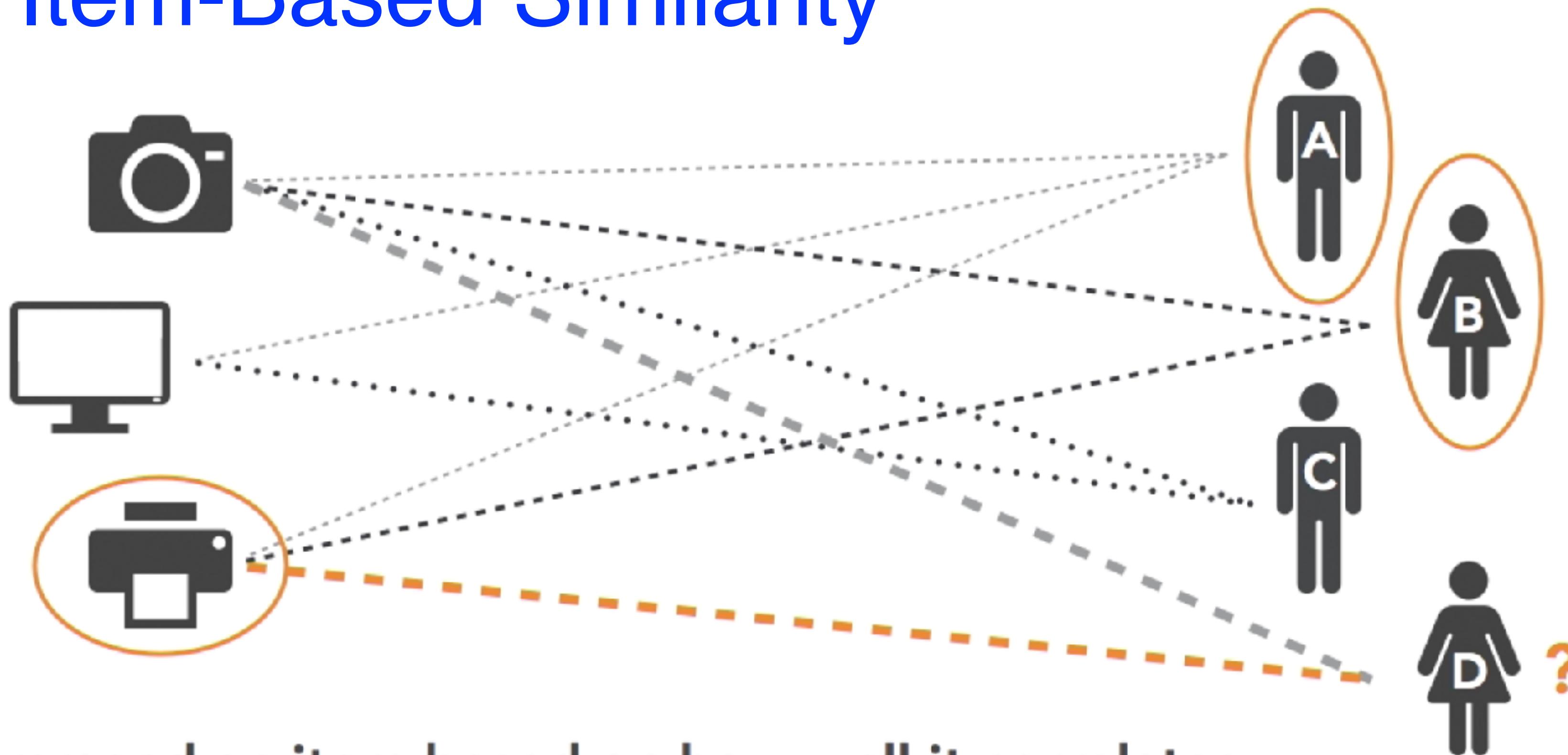
## Pearson correlation coefficient ( $r$ )

- $r = 1 \rightarrow$  Strong positive *linear* relationship
- $r = 0 \rightarrow$  Not linearly correlated
- $r = -1 \rightarrow$  Strong negative *linear* relationship



# Correlation-Based Recommendation Systems

## Item-Based Similarity



**Recommend an item based on how well it correlates  
with other items with respect to user ratings**



# Classification-based Collaborative Filtering

- Naive Bayes classification
- Logistic regression



A simple machine learning method you can use to predict the value of a numeric categorical variable based on its relationship with predictor variables



# Classification-based Collaborative Filtering

Provides personalization by accepting



User and item attribute data



Purchase history data



Other contextual data



YES  
NO



**Will she purchase?**



# A Logistic Regression Recommender

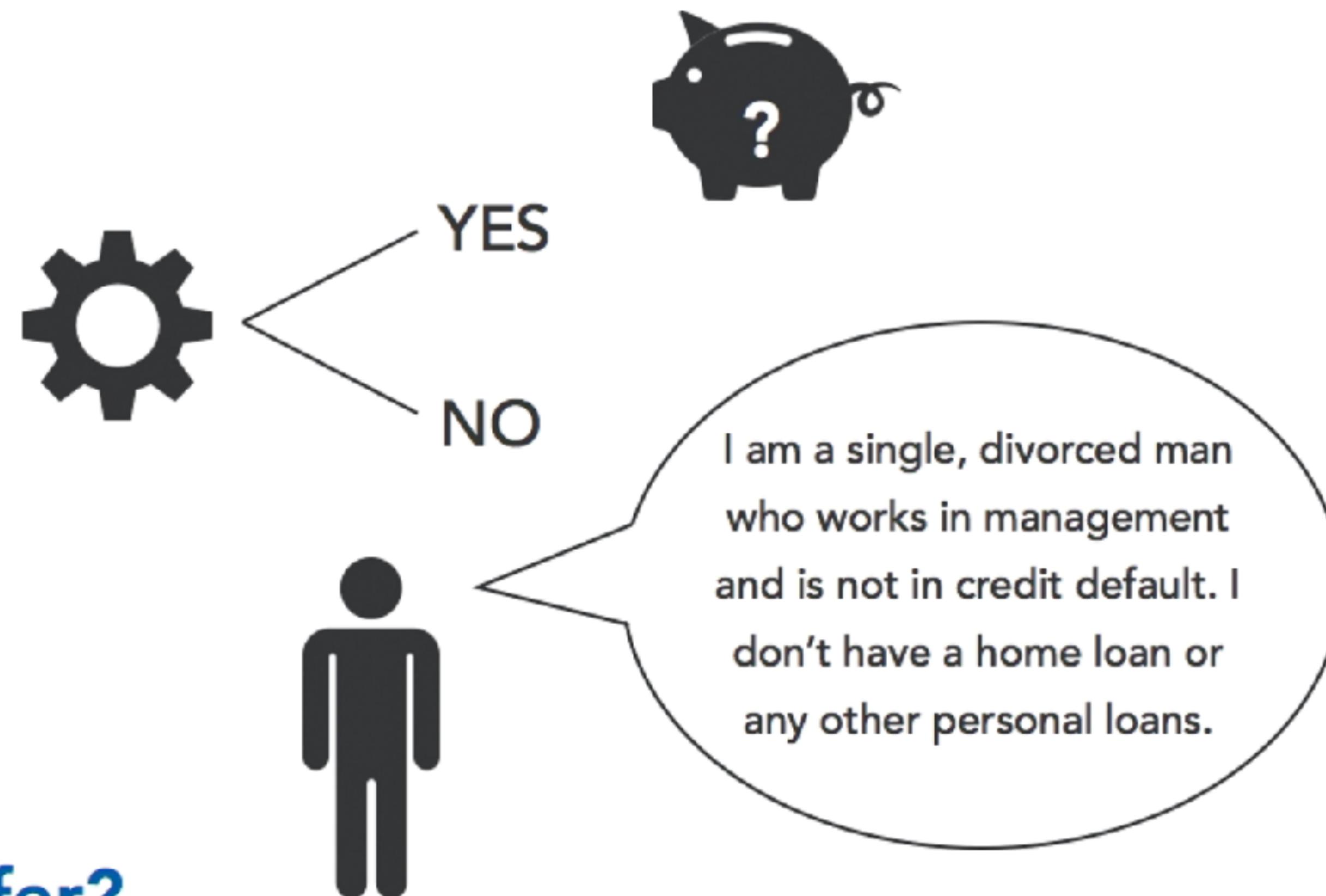


Transaction history



User attribute data

**Will he accept the offer?**





# A Logistic Regression Recommender

"I am a single, divorced man who works in management and is not in credit default. I don't have a home loan or any other personal loans... Also, no one from your marketing department has ever solicited me before."

housing_loan	credit_in_default	personal_loans	prev_failed_to_subscribe	prev_subscribed	job_management	job_tech	job_entrepreneur
0	0	0	0	0	1	0	0

job_bluecollar	job_unknown	job_retired	job_services	job_self_employed	job_unemployed	job_maid	job_student
0	0	0	0	0	0	0	0

married	single	divorced
0	1	1



[0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1]



# Model-Based Collaborative Filtering

- With model-based collaborative filtering systems, you build a recommender model from user ratings, and then make recommendations based on that model.



# Model-Based Collaborative Filtering

## Utility Matrix

Items	Item 1	Item 2	Item 3	Item 4	Item 5	Item 6
Users						
User A						
User B						
User C						
User D						
User E						

Sparse matrices!



# Model-Based Collaborative Filtering

## Singular Value Decomposition (SVD)

- A linear algebra method that can decompose a utility matrix into three compressed matrices
- Model-based recommender – use these compressed matrices to make recommendations without having to refer back to the complete data set
- Latent variables – inferred, nonobservable variables that are present within, and affect the behavior of a data set



# Model-Based Collaborative Filtering

## The Anatomy of SVD

$$\mathbf{A} = \mathbf{u} \times \mathbf{S} \times \mathbf{v}$$
$$\begin{bmatrix} & \end{bmatrix} = \begin{bmatrix} & \end{bmatrix} \times \begin{bmatrix} & \end{bmatrix} \times \begin{bmatrix} & \end{bmatrix}$$

**A**                            **u**                            **S**                            **v**

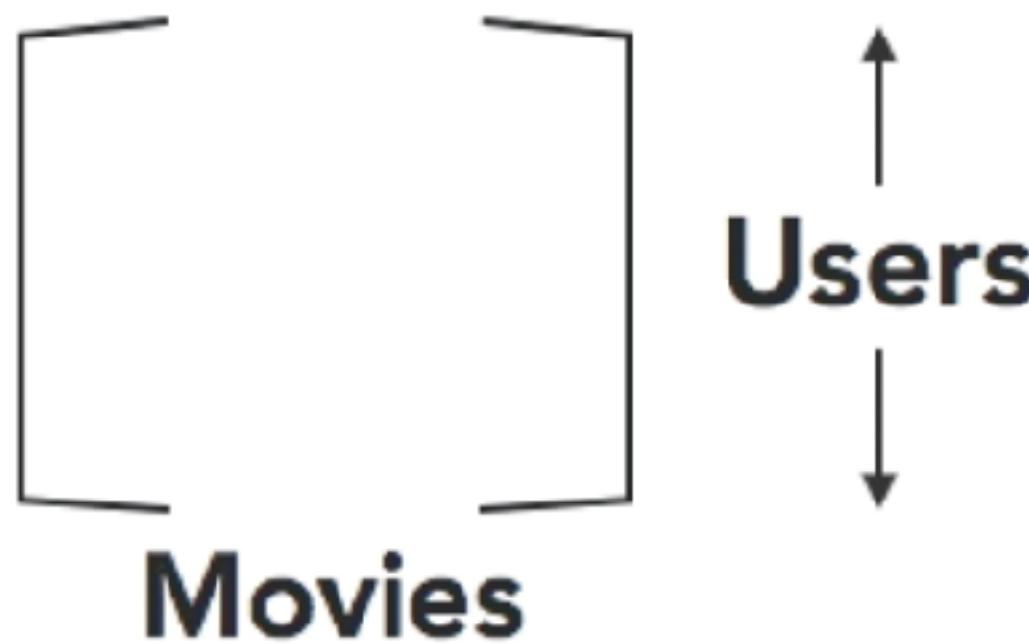
$$\mathbf{A} = \mathbf{u} \times \mathbf{S} \times \mathbf{v}$$

- **A** = Original matrix (utility matrix)
- **u** = Left orthogonal matrix – holds important, nonredundant information about users
- **v** = Right orthogonal matrix - holds important, non-redundant information on items.
- **S** = Diagonal matrix – contains all of the information about the decomposition processes performed during the compression



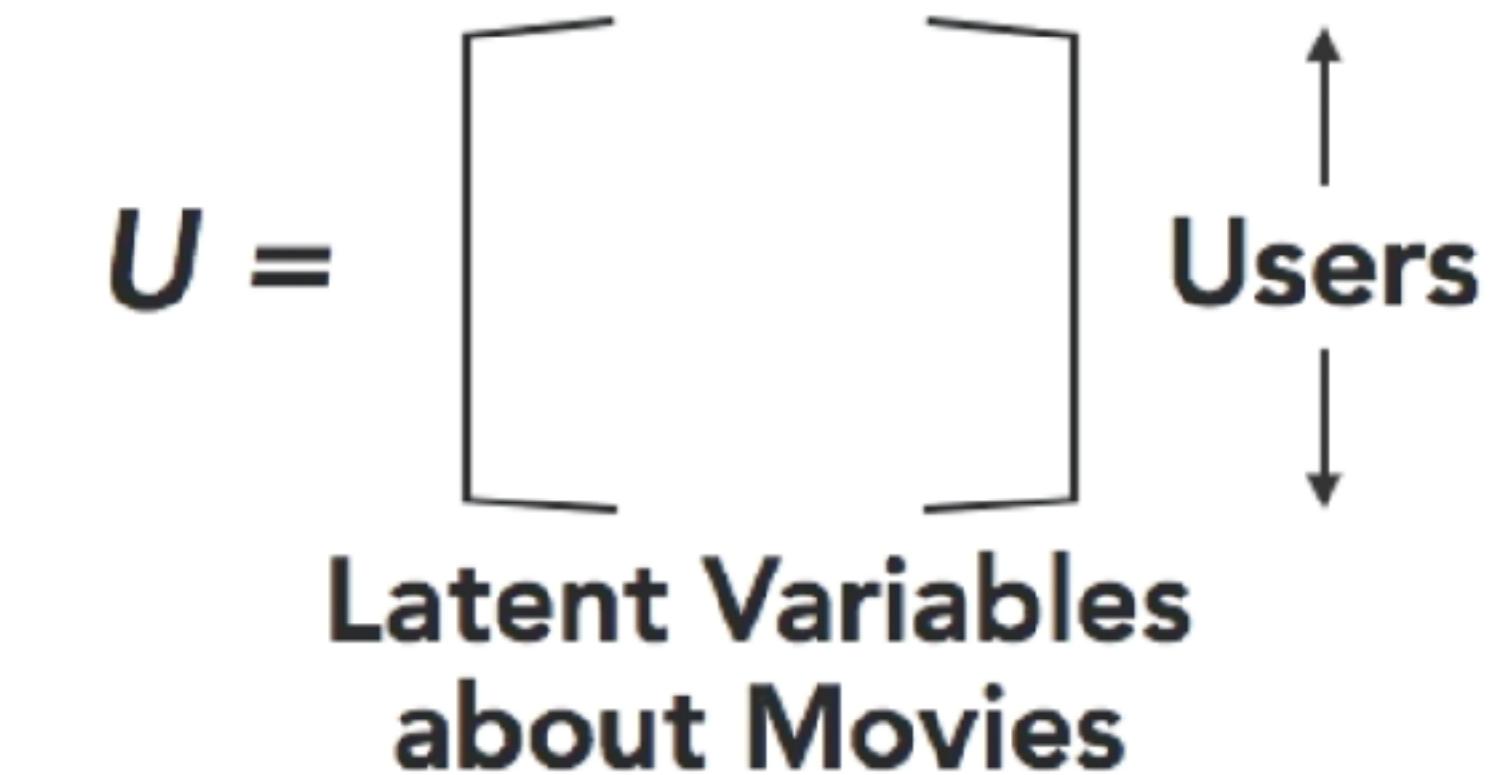
# Model-Based Collaborative Filtering

**943 x 1,664**

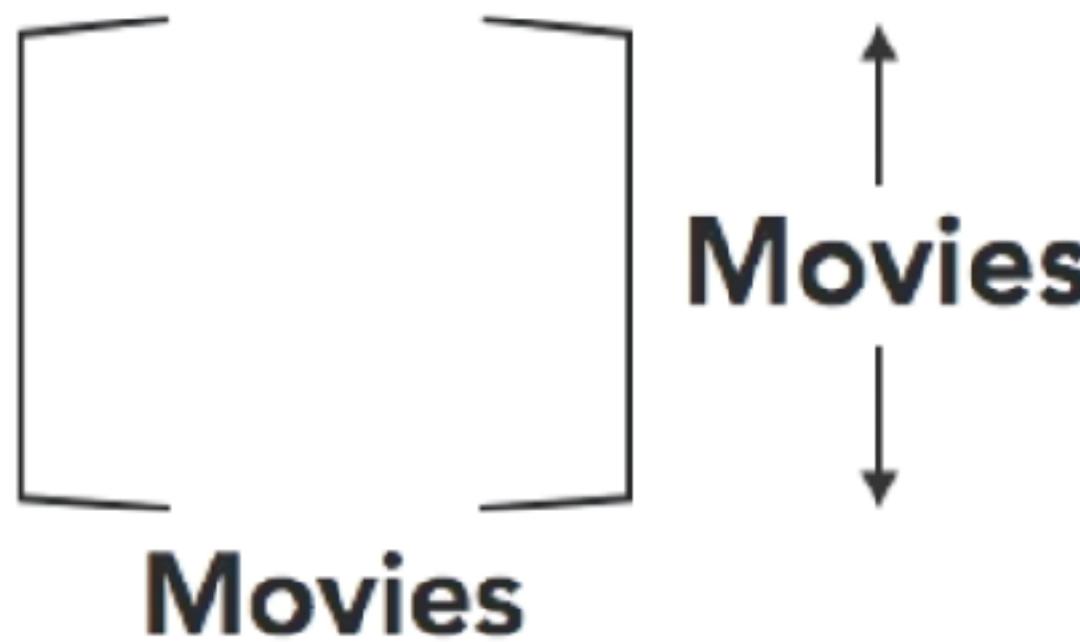


**n\_components=12**

**943 x 12**

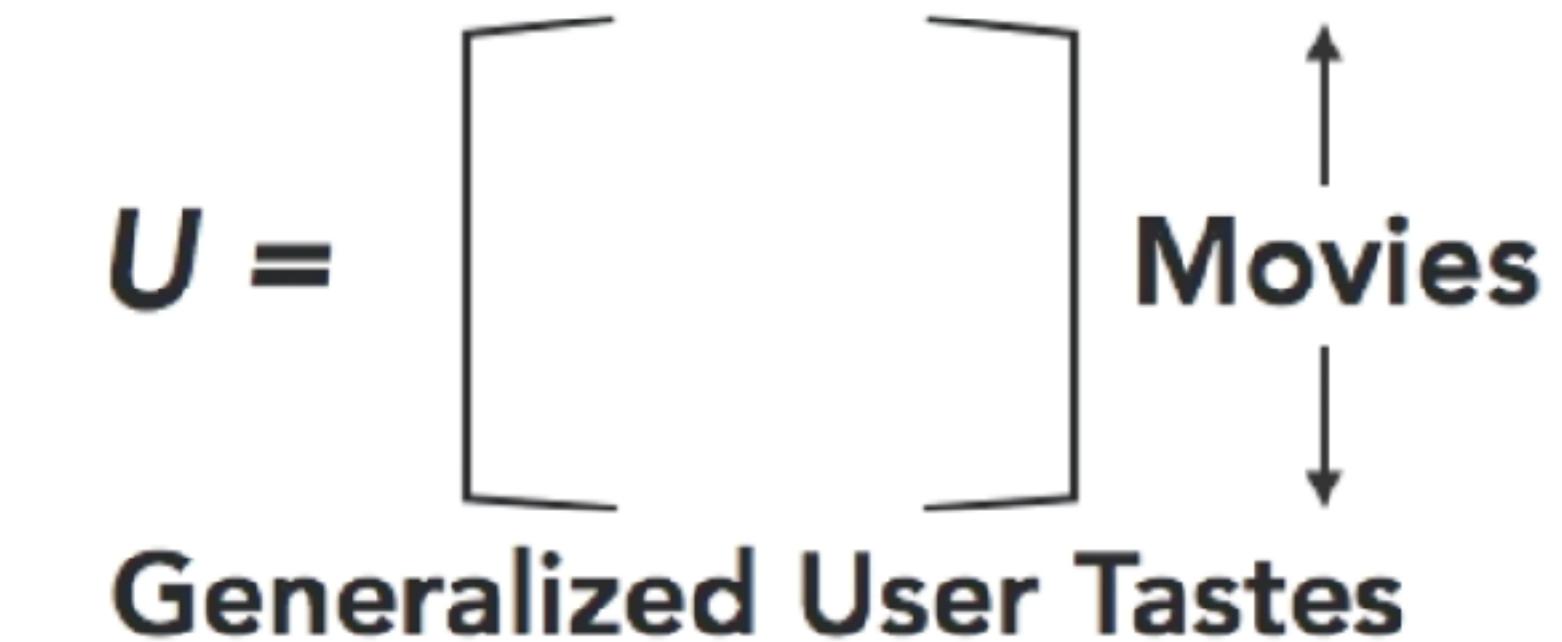


**1,664 x 943**



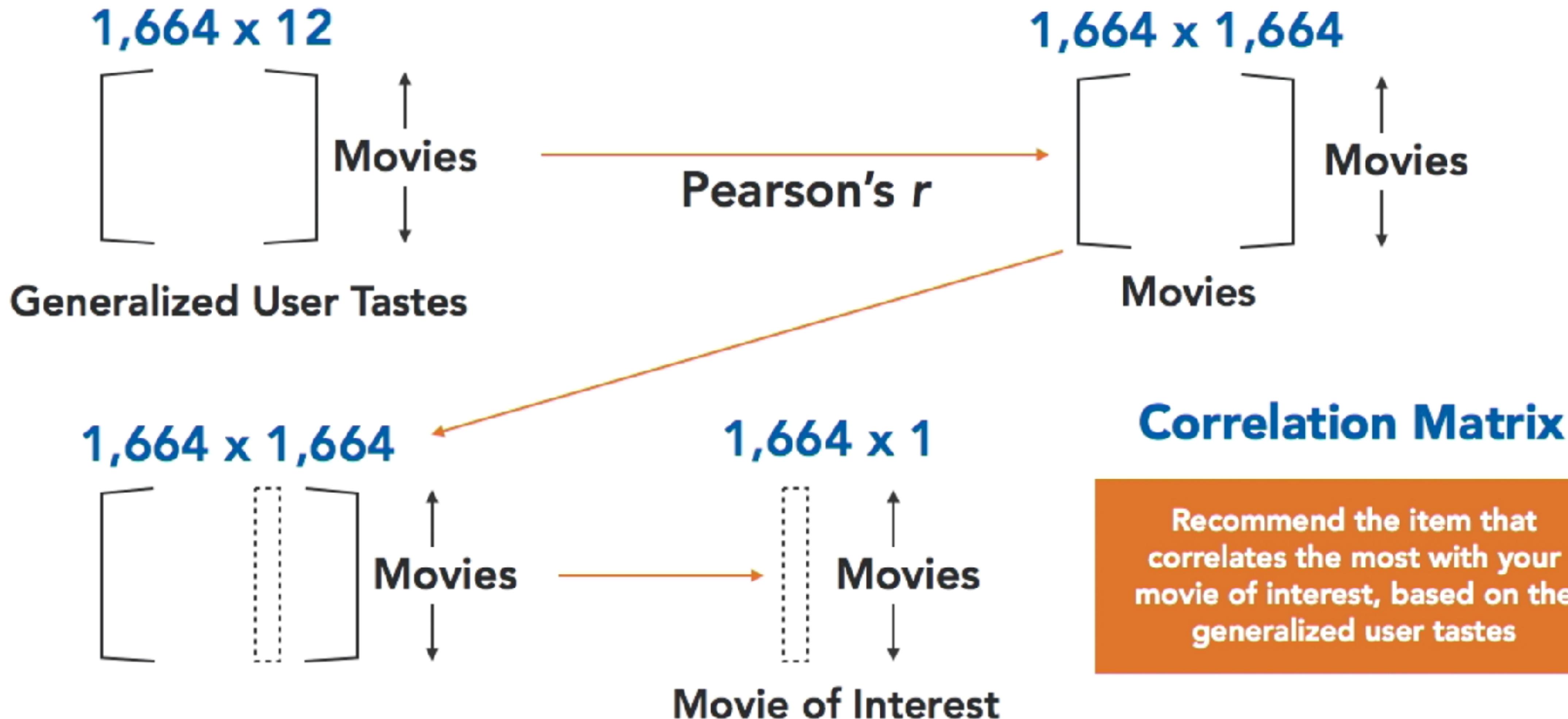
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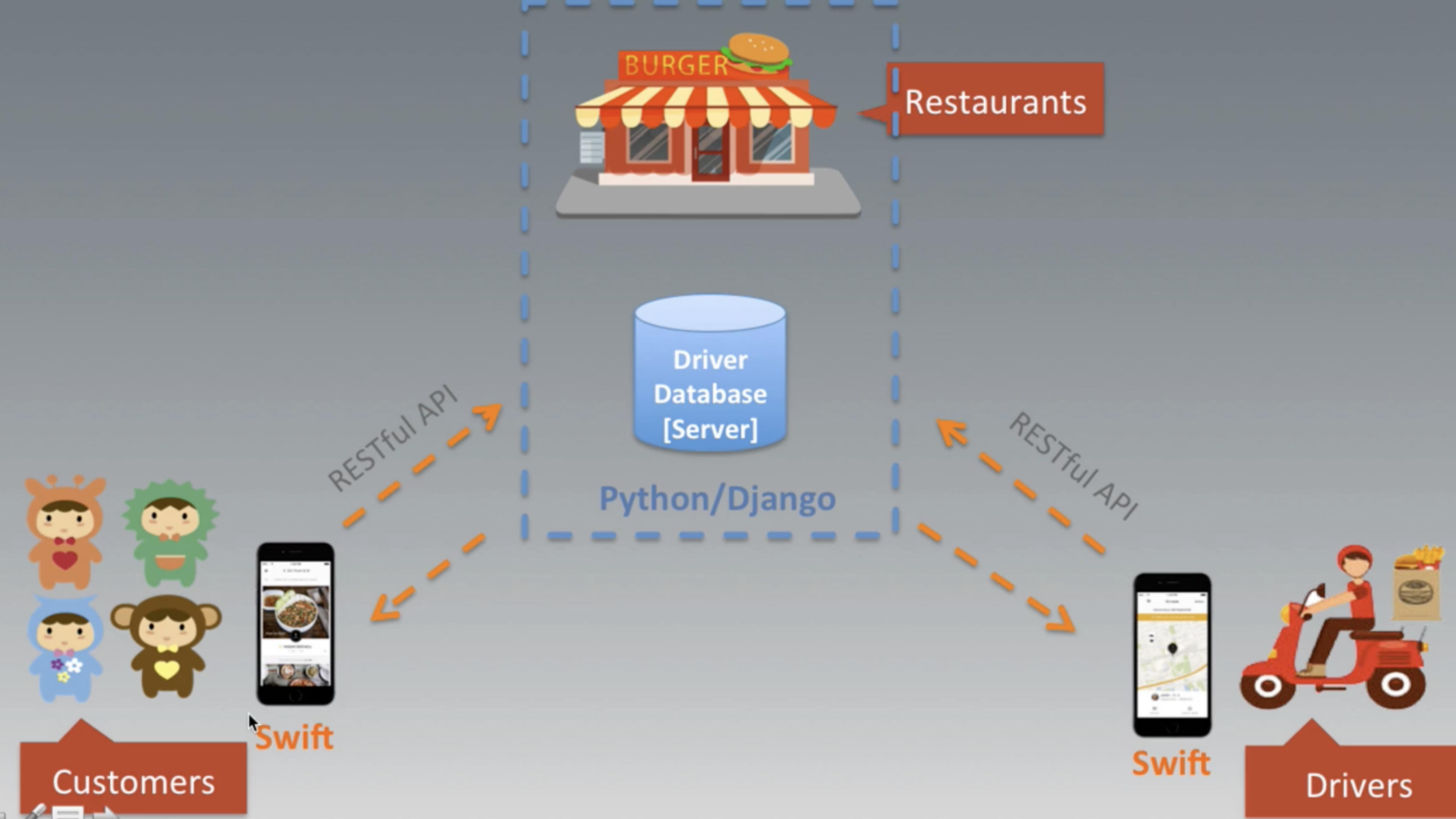
**1,664 x 12**





# Model-Based Collaborative Filtering





# SO, WHAT IF I WANT TO LEARN HOW TO BUILD DATA

Code4Startup



One Month

Udemy

treehouse™

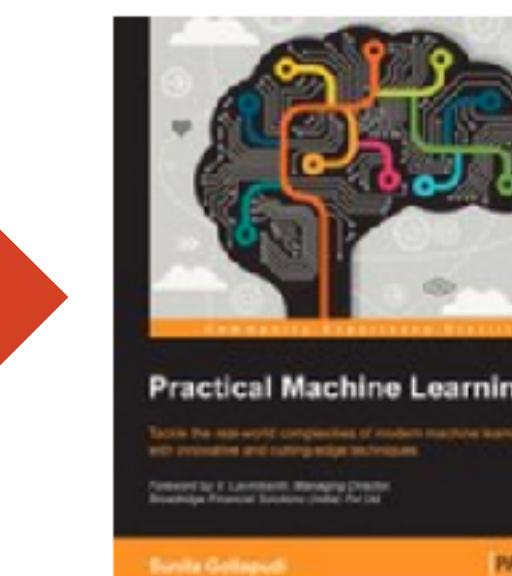


coursera



Code School  
a Pluralsight company

codecademy



# CHALLENGE YOURSELF WITH REAL-WORLD ML

kaggle

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## Welcome to Kaggle Competitions

Challenge yourself with real-world machine learning problems



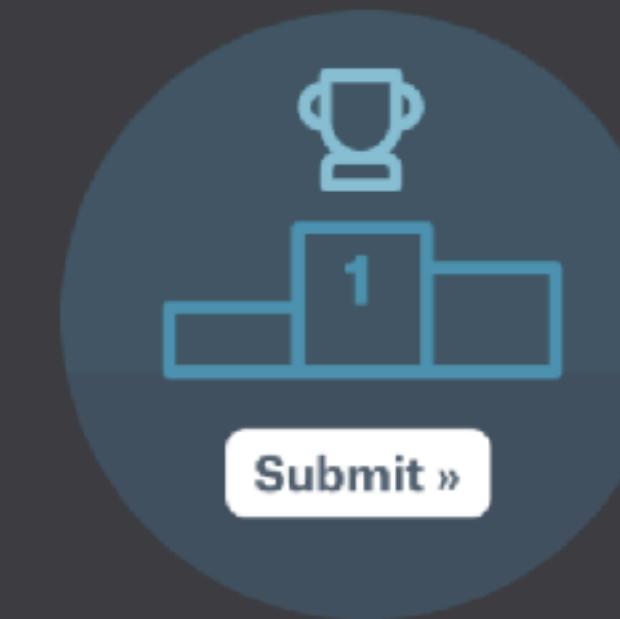
### New to Data Science?

Get started with a tutorial on our most popular competition for beginners, [Titanic: Machine Learning from Disaster](#).



### Build a Model

Get the data & use whatever tools or methods you prefer to make predictions.



### Make a Submission

Upload your prediction file for real-time scoring & a spot on the leaderboard.