CSE/STAT 416

Dimensionality Reduction & Recommender Systems Intro

Pre-Class Videos

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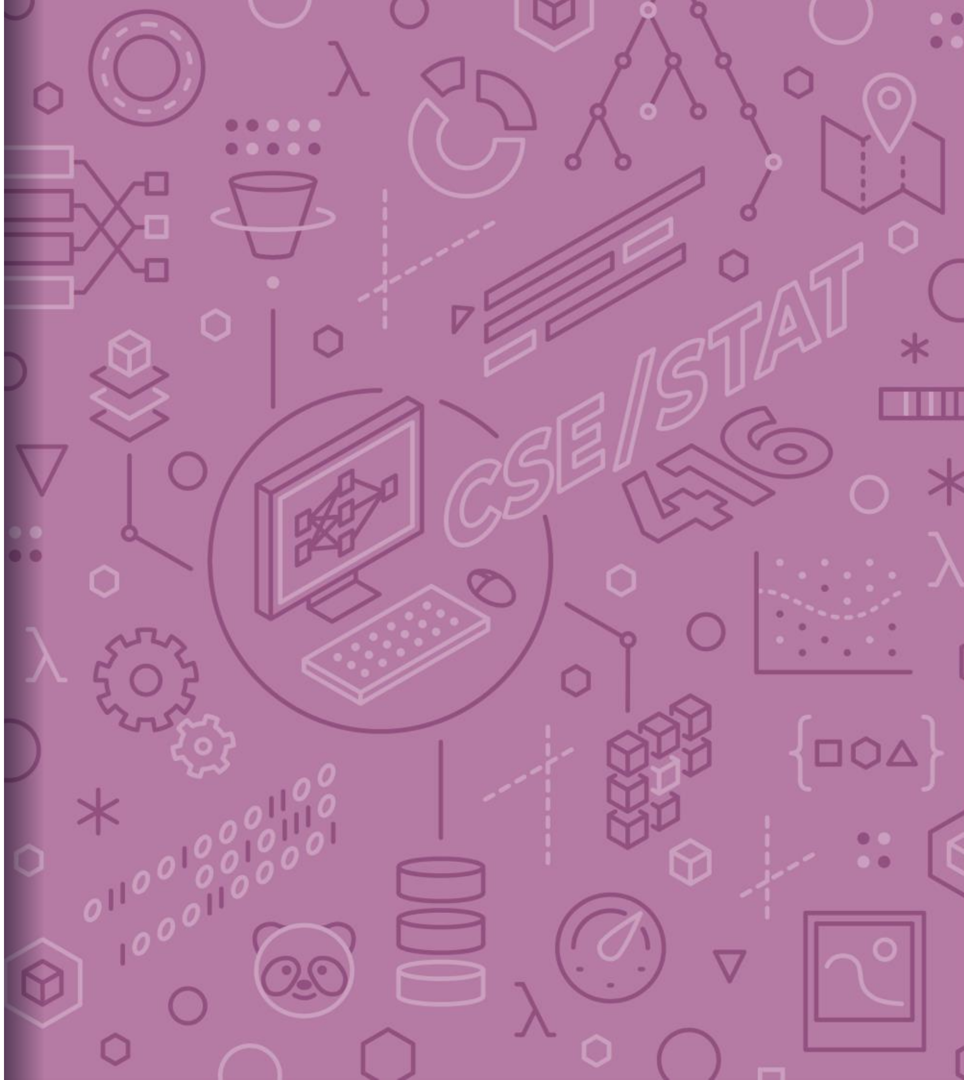
Aug 5, 2024

❓ **Questions?** Raise hand or **sli.do #cs416**
🎵 **Listening to:** Still Woozy



Personalization

Personalization is transforming our experience of the world

- Youtube
- Netflix
- Amazon
- Spotify
- Facebook
- Many more…

Almost all have share a common trait where there are users that use the system and items that we want the user to look at.

A recommender system recommends items to a user based on what we think will be the most “useful” for the user.

Recommender System Challenges

Types of Feedback

Explicit - User tells us what she likes

Implicit – We try to infer what she likes from usage data

Top-k vs Diverse Outputs

Top-k recommendations might be very redundant

- Someone who likes Rocky I also will likely enjoy Rocky II, Rocky III, Rocky IV, Rocky V

Diverse Recommendations

- Users are multi-faceted & we want to hedge our bets
- Maybe recommend: Rocky II, Always Sunny in Philadelphia, Robin Hood

Cold Start

When a new movie comes into our system, we don't know who likes it! This is called the **cold start** problem.

Generally, to solve we will need "side information"

- Genre, actors, if it's a sequel

Could also try to test users to see if they like it to learn quickly

That’s So Last Year

Interests change over time

- Is it 1967?
- Or 1977?
- Or 1998?
- Or 2011?

Models need flexibility to adapt to users

- Macro scale
- Micro scale (fads)

Scalability

For N users and M movies, some approaches take $\mathcal{O}(N^3 + M^3)$ time. This can be prohibitively slow for billions of users.

Big focus has been on:

- Efficient implementations
- Exact or faster approximate methods as needed

Popularity

Solution 0

Popularity

Simplest Approach: Recommend whatever is popular

- Rank by global popularity (i.e. Avengers Endgame)

Limitations

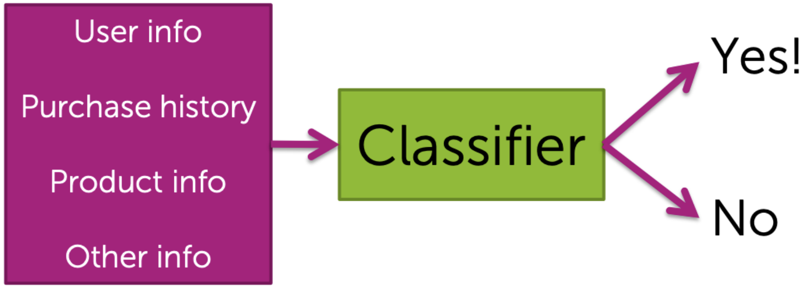
- No personalization
- Feedback loops

Classification Model

Solution 1

Learn a Classifier

Train a classifier to learn whether or not someone will like an item

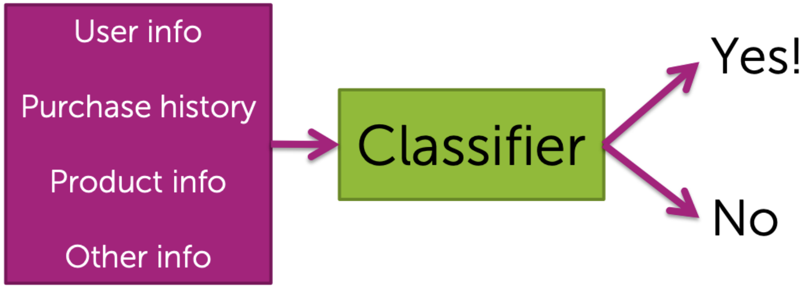


Pros

- Personalized
- Features can capture context (time of day, recent history, ...)
- Can even handle limited user history (age of user, location, ...)

Learn a Classifier

Train a classifier to learn whether or not someone will like an item



Cons

- Features might not be available or hard to work with
- Often doesn't perform well in practice when compared to more advanced techniques like **collaborative filtering**
- Can still lead to feedback loops.

Roadmap

We will learn more advanced ideas for recommendation. Before that, we want to explore a slightly unrelated idea of dimensionality reduction.

- This will be useful in helping us think about some key ideas for what can make recommendation useful.
- A very general/powerful tool useful in other ML applications.

Today:

- Recommender System Intro
- Dimensionality Reduction (PCA)

Wednesday

- Matrix Factorization

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Dimensionality Reduction & Recommender Systems Intro

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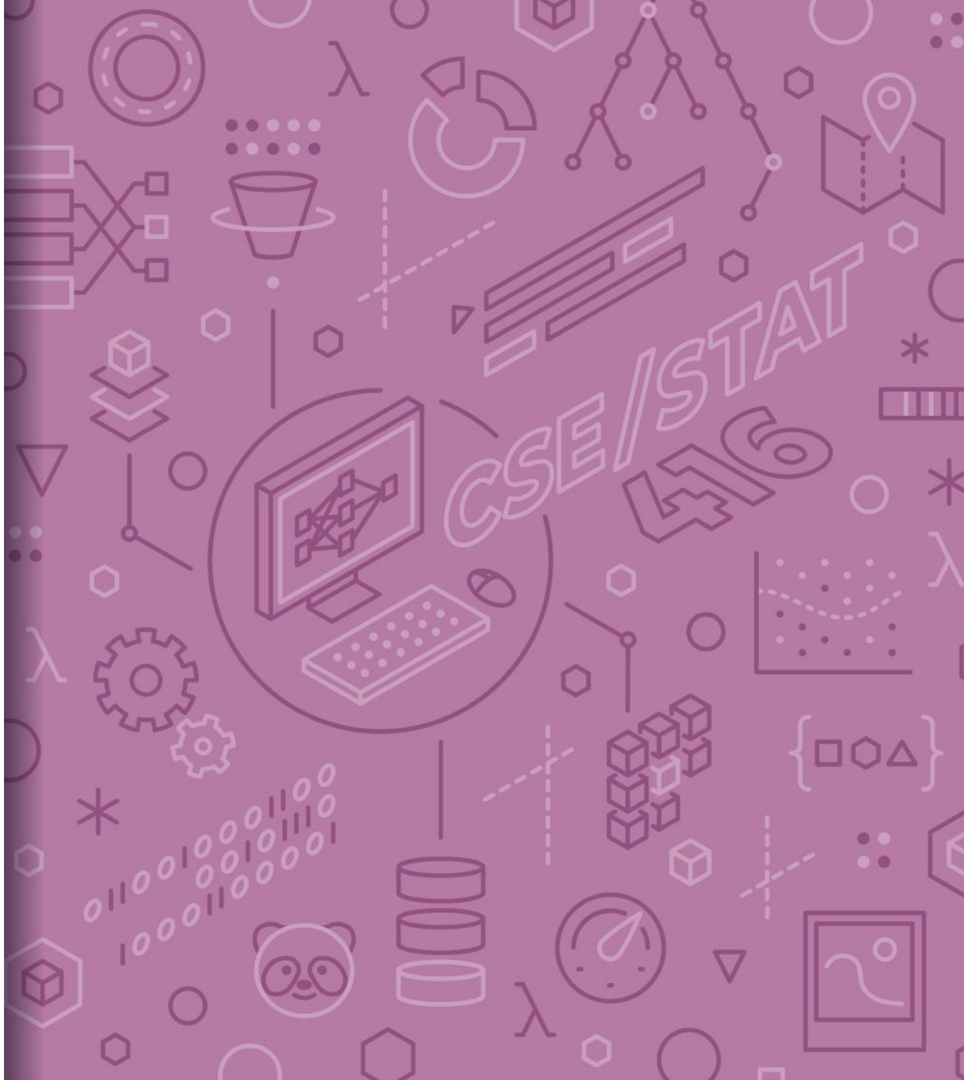


Dimensionality Reduction

Large Dimensionality

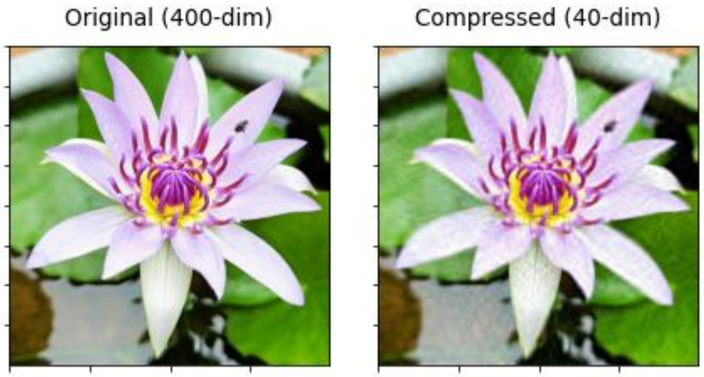
Input data might have thousands or millions of dimensions!

- **Images**: 200x200 image is 120,000 features!
- **Text**: # features = # n-grams 😮
- **Course Success**: dozen(s) of features
- **User Ratings**: 100s of ratings (one per rate-able item)

	Area Abbreviation	Area Code	Area	Item Code	Item	Element Code	Element	Unit	latitude	longitude	...	Y2004
0	AF	2	Afghanistan	2511	Wheat and products	5142	Food	1000 tonnes	33.94	67.71	...	3249.0
1	AF	2	Afghanistan	2805	Rice (Milled Equivalent)	5142	Food	1000 tonnes	33.94	67.71	...	419.0
2	AF	2	Afghanistan	2513	Barley and products	5521	Feed	1000 tonnes	33.94	67.71	...	58.0
3	AF	2	Afghanistan	2513	Barley and products	5142	Food	1000 tonnes	33.94	67.71	...	185.0
4	AF	2	Afghanistan	2514	Maize and products	5521	Feed	1000 tonnes	33.94	67.71	...	120.0

Issues with Too Many Dimensions

- **Visualization**: Hard to visualize more than 3D.
- **Overfitting**: Greater risk of overfitting with more features/dimensions
- **Scalability**: some ML approaches (e.g., k-nn, k-means) perform poorly in high-dimensional spaces (curse of dimensionality)
- **Redundancy**: high-dimensional data often occupies a lower-dimensional subspace.
  - Most pixels in MNIST (digit recognition) are white – are they necessary?
    - Image Compression



Dimensionality Reduction

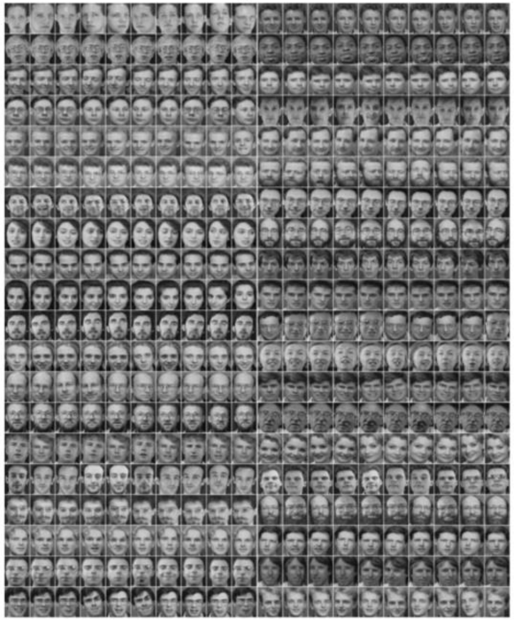
Dimensionality Reduction is the the task of representing the data with a fewer number of dimensions, while keeping meaningful relations between data

Example: Embedding Pictures

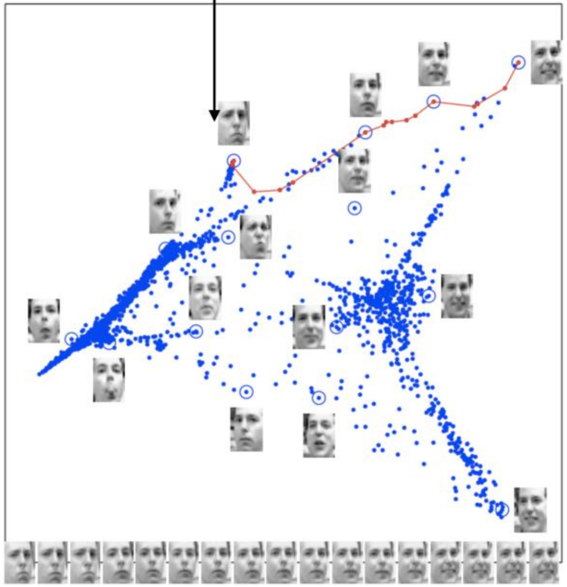
Example: Embed high dimensional data in low dimensions to visualize the data

- Goal: Similar images should be near each other.

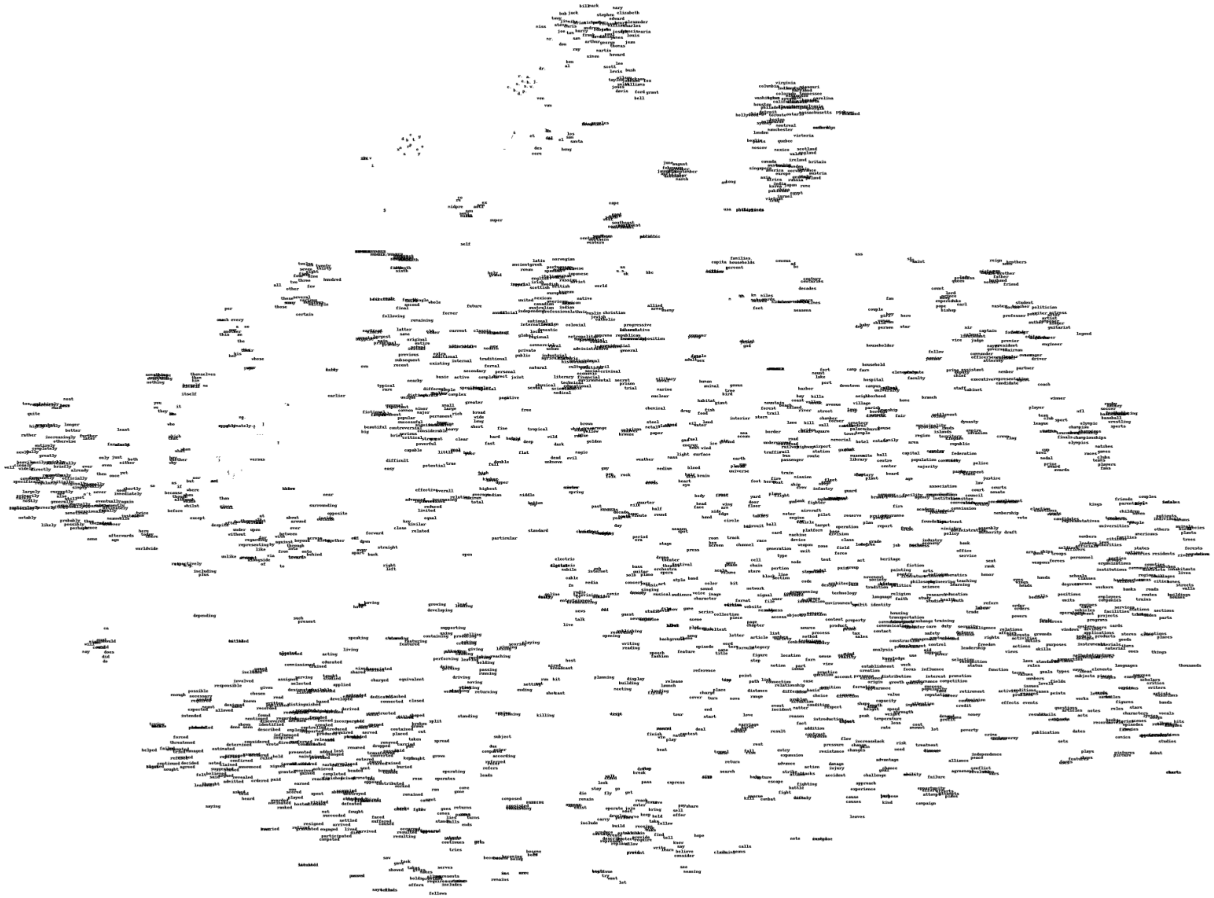
Input data image



2-dimensional embedding



Example: Embedding Words



Example: Embedding Words

Principal Component Analysis (PCA)

One very popular dimensionality reduction algorithm is called **Principal Component Analysis (PCA)**.

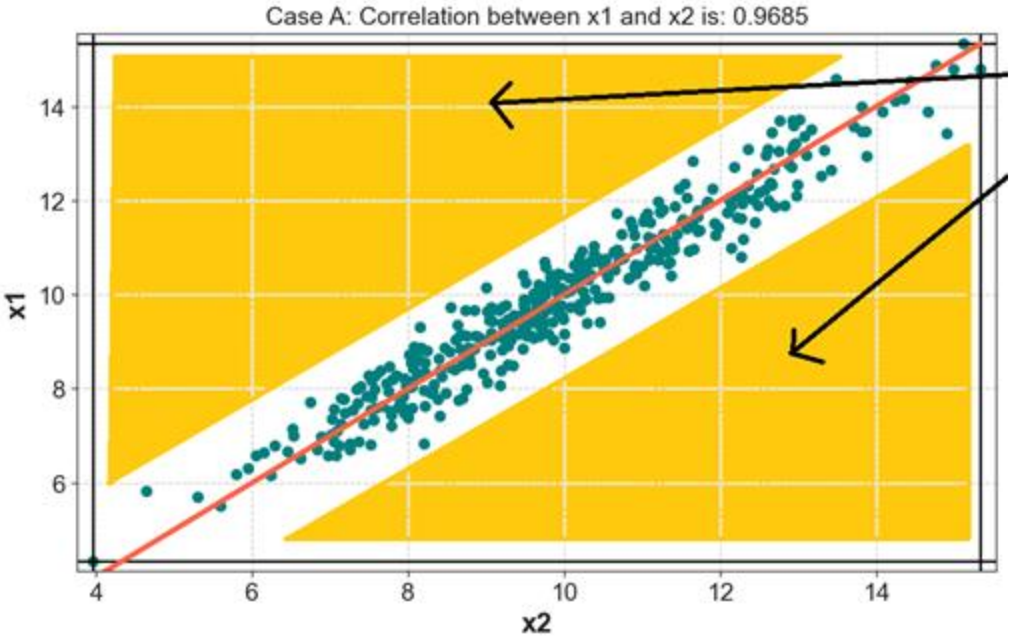
Idea: Use a linear projection from d-dimensional data to k-dimensional data

- E.g. 1000 dimension word vectors to 3 dimensions

Choose the projection that minimizes **reconstruction error**

- Idea: The information lost if you were to ”undo” the projection

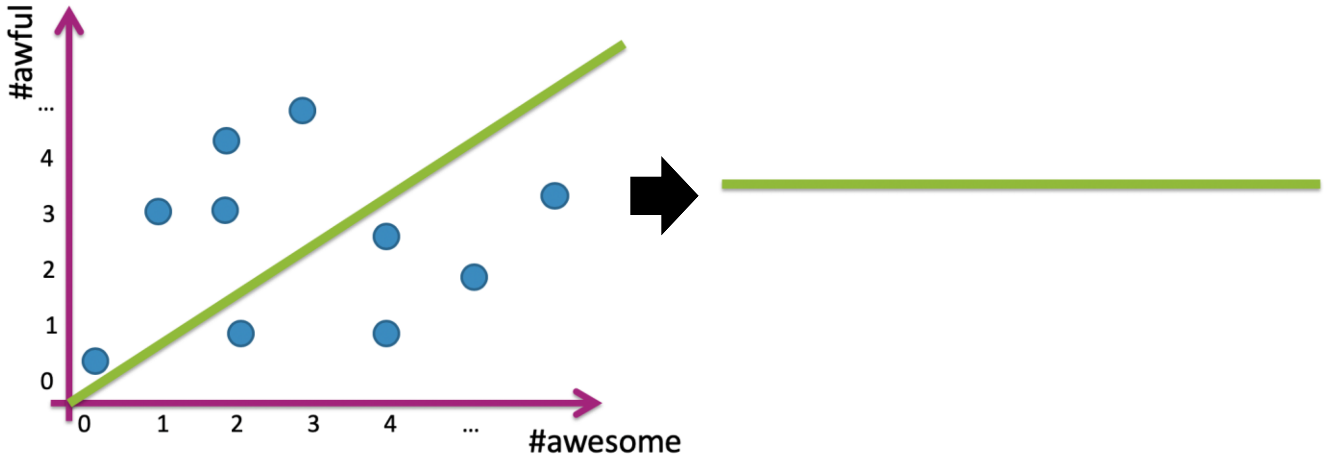
Principal Component Analysis (PCA)



Regions with no data. Data exists close to a lower-dimensional subspace.

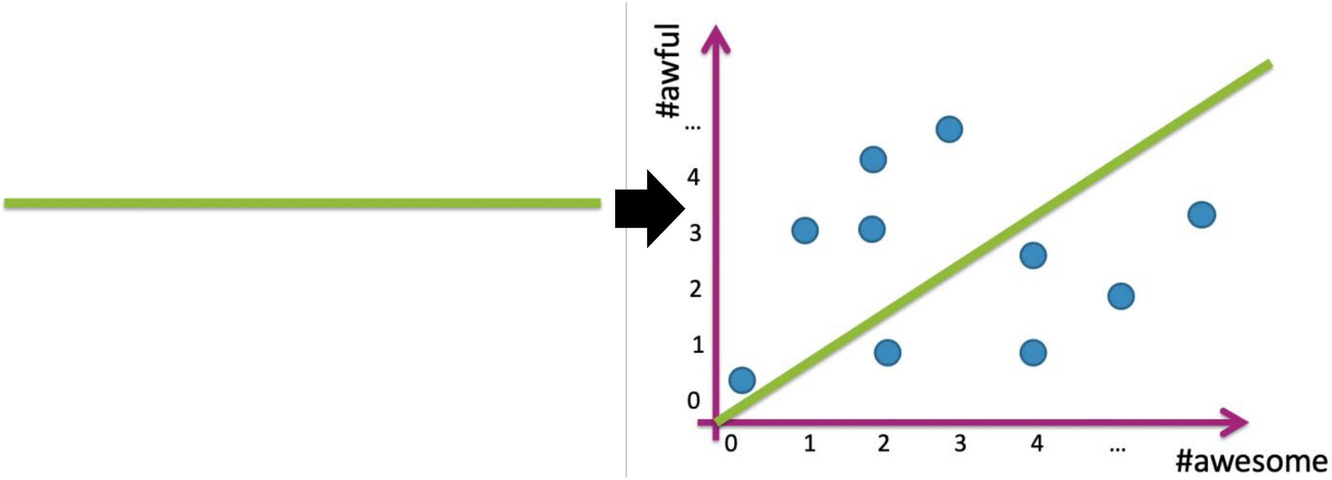
Linear Projection

Project data into 1 dimension along a line



Reconstruction

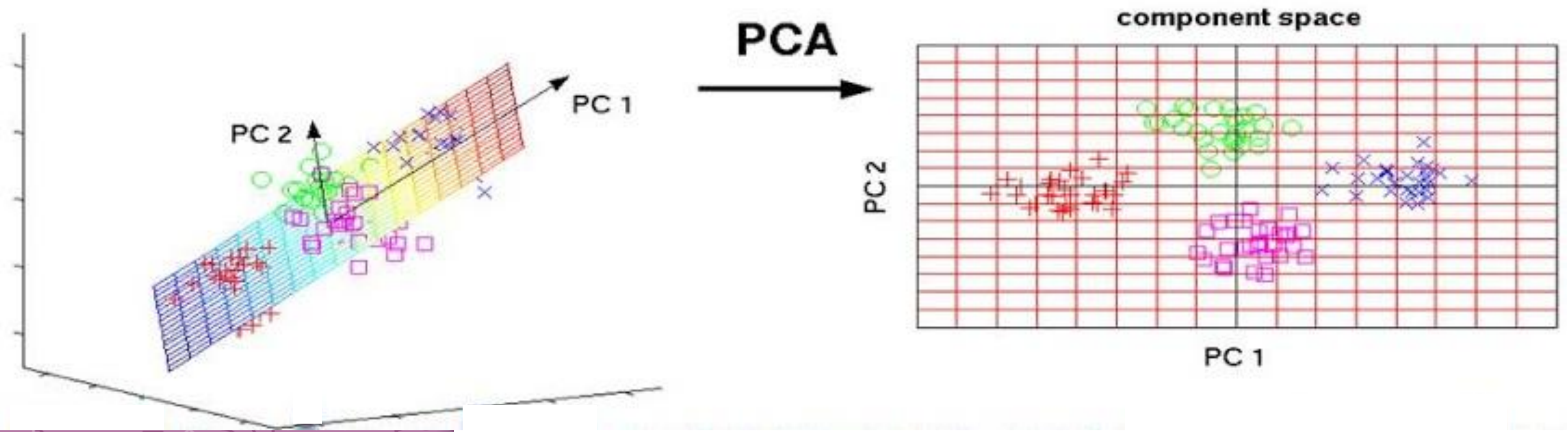
Reconstruct original data only knowing the projection



Linear Projection in Higher Dimensions

Think of PCA as giving each datapoint a new "address."

- Earlier, you could find the datapoint by going to the location (x, y, z).
- Now, if you are just moving in the projection plane, you can (approximately) find the datapoint by going to the location (u_1, u_2)



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Group

2 min

- Compute the 2D coordinates of the following point. Then compute its reconstruction error.
  - $x_i = [0, -7, 3, 2, 5]$
  - $u_1 = [-0.5, 0, 0.5, -0.5, 0.5]$
  - $u_2 = [0.5, 0, 0.5, -0.5, -0.5]$
  - $z_i = ??$
  - $\hat{x}_i = ??$
  - $\|\hat{x}_i - x_i\|_2^2 = ??$

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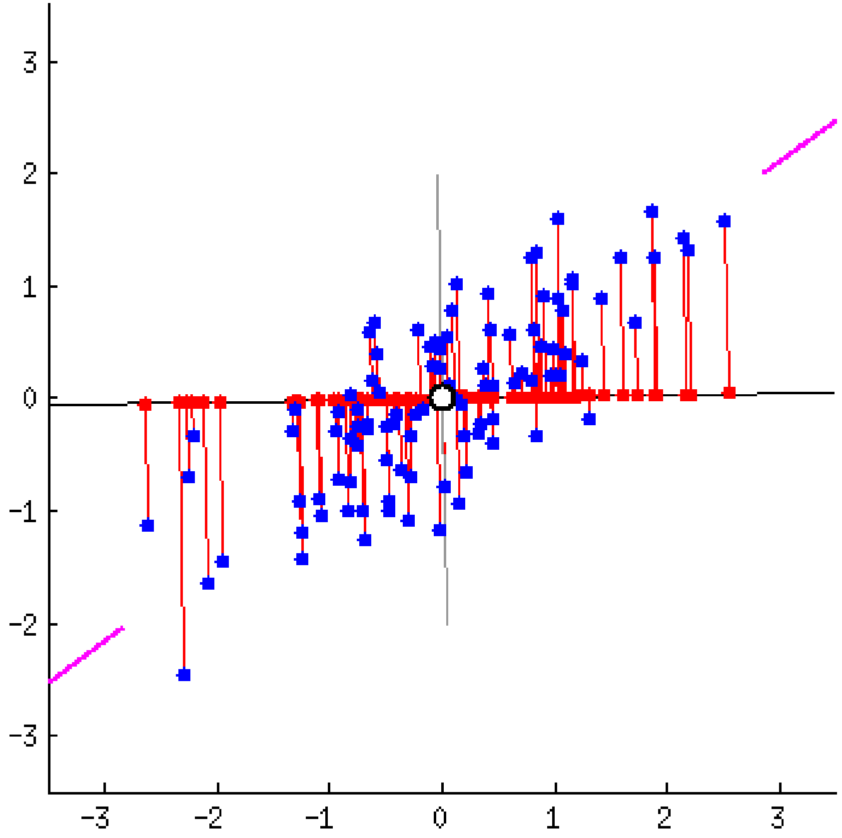
Group

2 min

- Compute the 2D coordinates of the following point. Then compute its reconstruction error.
  - $x_i = [0, -7, 3, 2, 5]$
  - $u_1 = [-0.5, 0, 0.5, -0.5, 0.5]$
  - $u_2 = [0.5, 0, 0.5, -0.5, -0.5]$
  - $z_i = ??$
  - $\hat{x}_i = ??$
  - $\|\hat{x}_i - x_i\|_2^2 = ??$

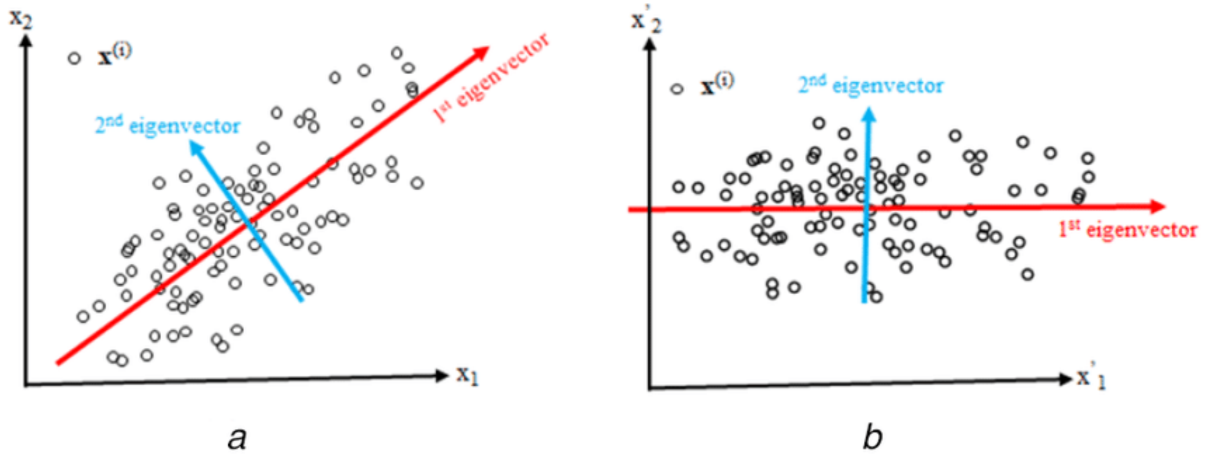
How do we find the best projection vector(s)?



Pick the vector(s) along which the datapoints have the most variation!

Eigenvectors

- There is a quantity in linear algebra that does exactly that!
- The **eigenvectors** of a d-dimensional dataset* are a collection of d *perpendicular* vectors that point in the directions of greatest variation amongst the points in the dataset.

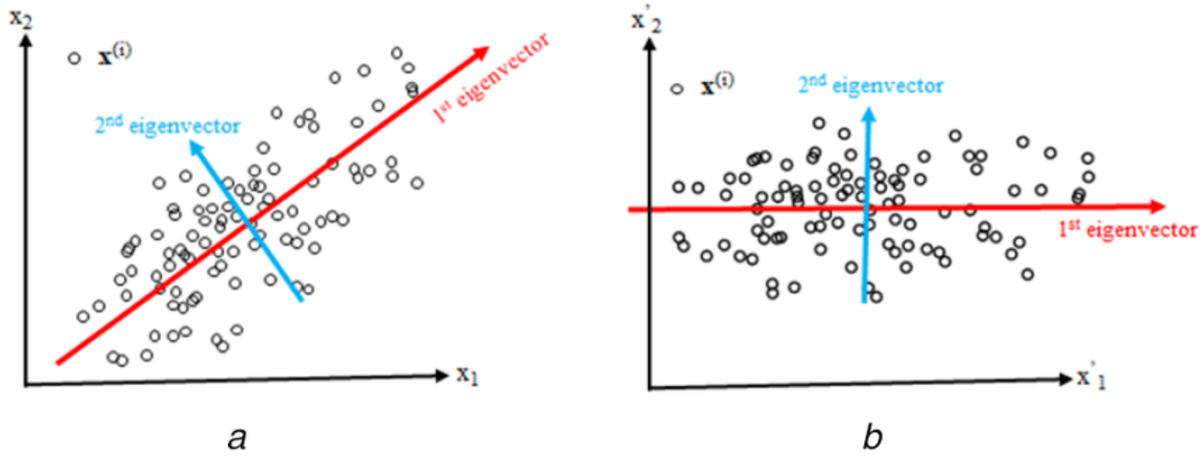


- Eigenvectors rotate the axes of the d dimensional space.

* (caveat) the eigenvectors are actually associated with the *covariance matrix* of the dataset

Eigenvalues

- Each eigenvector has a corresponding **eigenvalue**, indicating how much the dataset varies in that direction.
- Greater eigenvalue ➔ greater variance.



- **PCA**: Take the k eigenvectors with greatest eigenvalues.

PCA Algorithm

Input Data: An $\mathrm{n} \times d$ data matrix X

- Each row is an example

1. **Center Data**: Subtract mean from each row
$$X_c \leftarrow X - \bar{X}[1:d]$$
2. **Compute spread/orientation**: Compute covariance matrix Σ
$$\Sigma[t,s] = \frac{1}{n}\sum_{i=1}^{n} x_{c,i}[t]x_{c,i}[s]$$
3. **Find basis for orientation**: Compute eigenvectors of Σ
   - Select k eigenvectors $u_1, \dots, u_k$ with largest eigenvalues
4. **Project Data**: Project data onto principal components
$$z_i[1] = u_1^T x_{c,i} = u_1[1]x_{c,i}[1] + \cdots + u_1[d]x_{c,i}[d]$$
$$\dots$$
$$z_i[k] = u_k^T x_{c,i} = u_k[1]x_{c,i}[1] + \cdots + u_k[d]x_{c,i}[d]$$

Reconstructing Data

Using principal components and the projected data, you can reconstruct the data in the original domain.

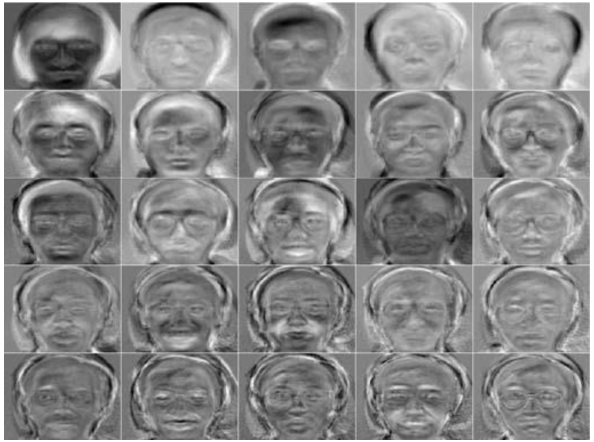
$$\hat{x}_i[1:d] = \bar{X}[1:d] + \sum_{j=1}^{k} z_i[j]\ u_j$$

Example: Eigenfaces

Apply PCA to face data

Input Data

Principal Components



Reconstructing Faces

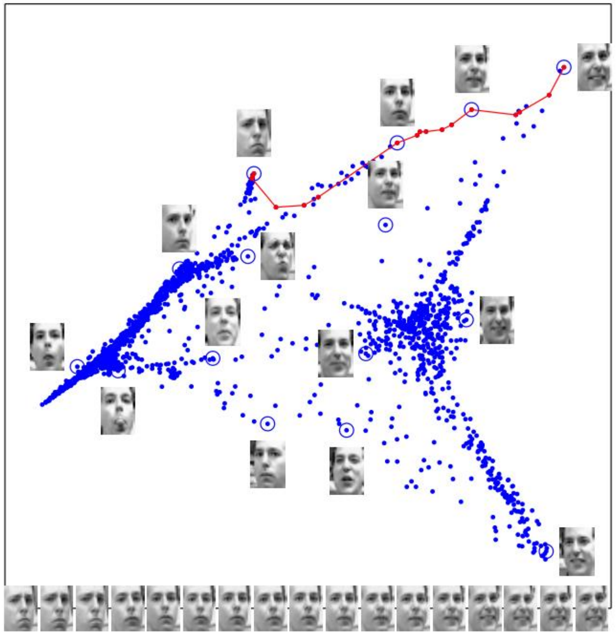
Depending on context, it may make sense to look at either original data or projected data.

In this case, let's see how the original data looks after using more and more principal components for reconstruction.

- Each image shows additional 8 principal components

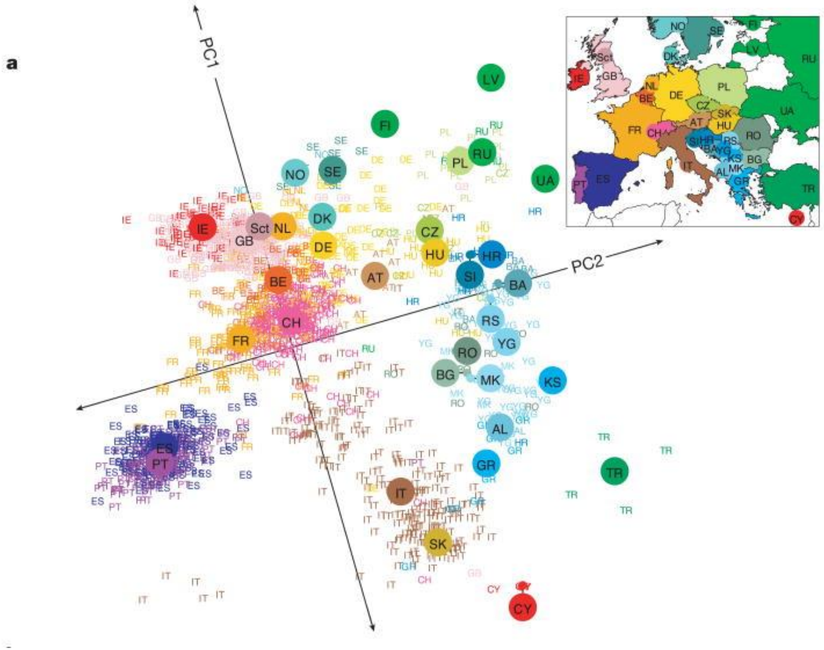
Embedding Images

Other times, it does make sense to look at the data in the projected space! (Usually if $k \leq 3$)



Example: Genes

Dataset of genes of Europeans (3192 people; 500,568 loci) and their country of origin, ran PCA on the data and plotted 2 principal components.



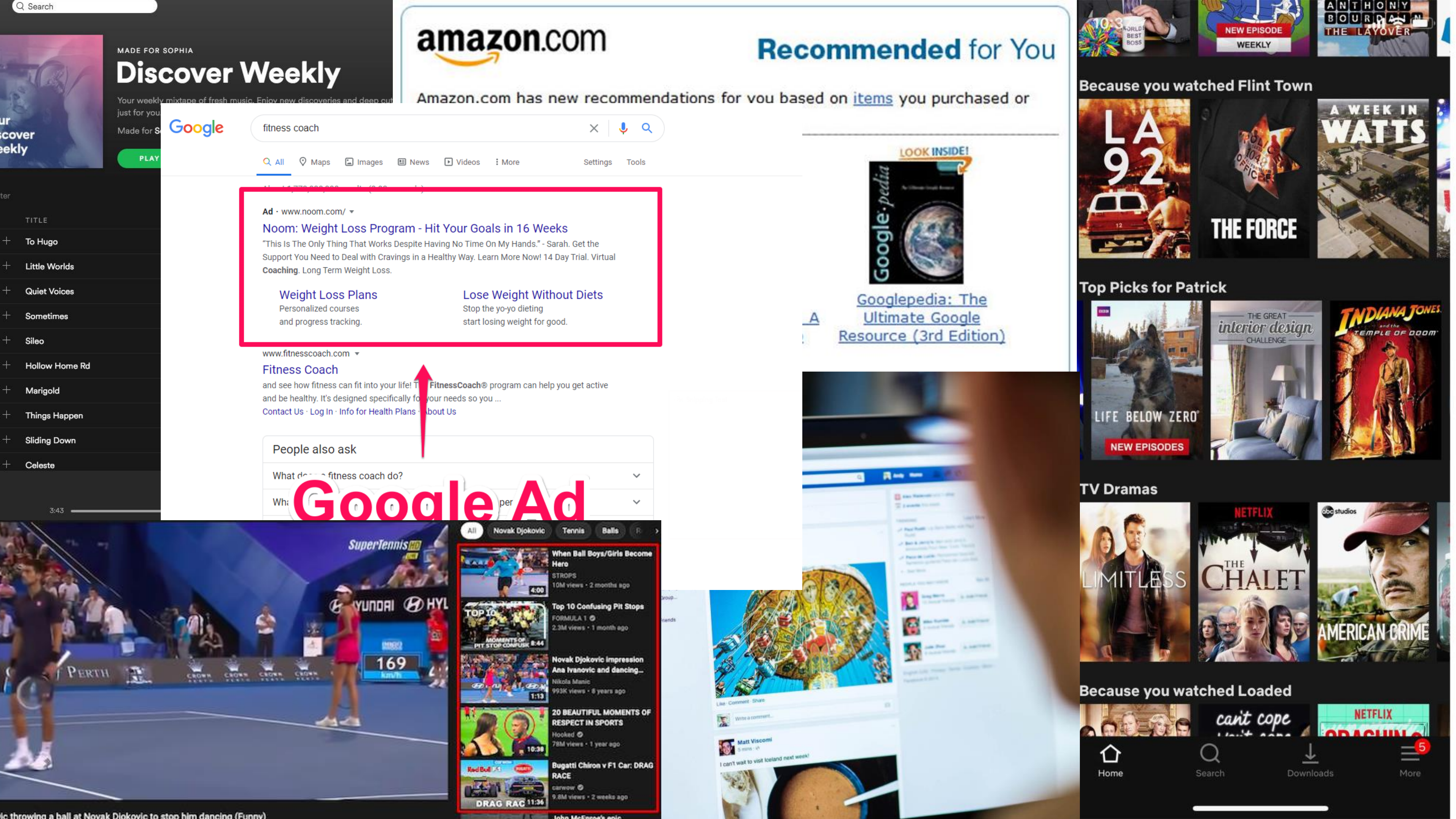
Brain Break

General Steps to Take as an ML Practitioner

Given a new dataset:

- Split into train and test sets.
- Understand the dataset:
  - Understand the feature/label types and values
  - Visualize the data: scatterplot, boxplot, PCA, clustering
- Use that intuition to decide:
  - What features to use, and what transformations to apply to them (pre-processing).
  - What model(s) to train.
- Train the models, evaluate them using a validation set or cross-validation.
- Deploy the best model.

Intro to Recommender Systems



Search
MADE FOR SOPHIA
Discover Weekly
TITLE
To Hugo
Little Worlds
Quiet Voices
Sometimes
Sileo
Hollow Home Rd
Marigold
Things Happen
Sliding Down
Celeste
3:43
amazon.com
Recommended for You
Amazon.com has new recommendations for you based on items you purchased or
LOOK INSIDE!
Googlepedia: The Ultimate Google Resource (3rd Edition)
Google
fitness coach
All
Maps
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Videos
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"This Is The Only Thing That Works Despite Having No Time On My Hands." - Sarah. Get the Support You Need to Deal with Cravings in a Healthy Way. Learn More Now! 14 Day Trial. Virtual Coaching. Long Term Weight Loss.
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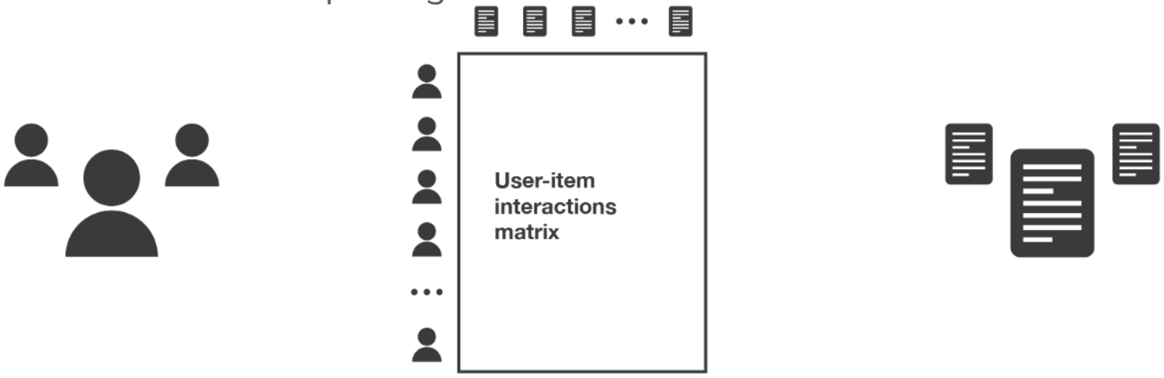
Tennis
Balls
SuperTennis
HYUNDAI
PERTH
169 km/h
When Ball Boys/Girls Become Hero
10M views · 2 months ago
Top 10 Confusing Pit Stops
FORMULA 1
2.3M views · 1 month ago
Novak Djokovic impression Ana Ivanovic and dancing...
Nikola Manic
993K views · 8 years ago
20 BEAUTIFUL MOMENTS OF RESPECT IN SPORTS
Hooked
78M views · 1 year ago
Bugatti Chiron v F1 Car: DRAG RACE
carwow
9.8M views · 2 weeks ago

Recommender Systems Setup

- You have n users and m items in your system
  - Typically, $n \gg m$. E.g., Youtube: 2.6B users, 800M videos
- Based on the content, we have a way of measuring user preference.
- This data is put together into a **user-item interaction matrix**.



Users	User-item interactions matrix	Items
suscribers	rating given by a user to a movie (integer)	movies
readers	time spent by a reader on an article (float)	articles
buyers	product clicked or not when suggested (boolean)	products
	...	

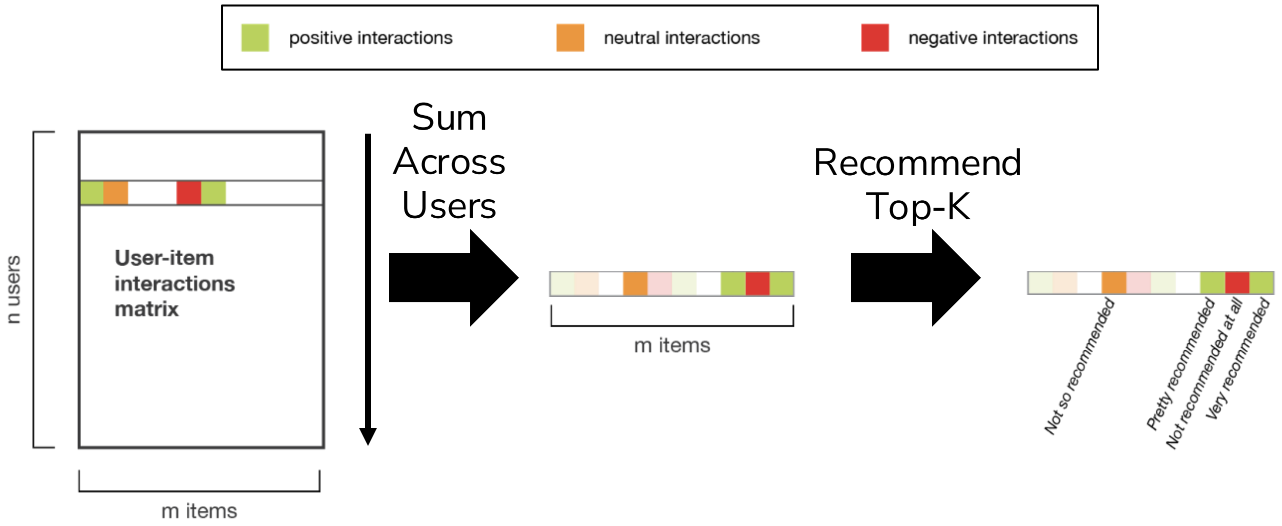
- **Task**: Given a user u_i or item v_j, predict one or more items to recommend.

Solution 0: Popularity

Solution 0: Popularity

Simplest Approach: Recommend whatever is popular

- Rank by global popularity (i.e., Squid Game)



Solution 0 (Popularity) Pros / Cons

Pros:

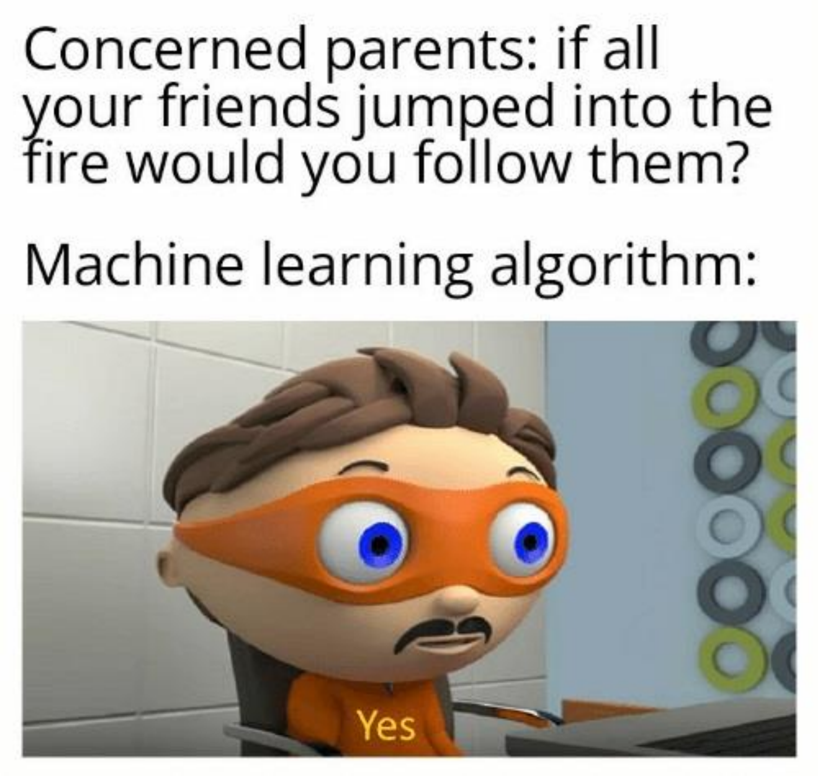
- Easy to implement

Cons:

- No Personalization
- Feedback Loops
- Top-K recommendations might be redundant
  - e.g., when a new Harry Potter movie is released, the others may also jump into top-k popularity.

Solution 1: Nearest User

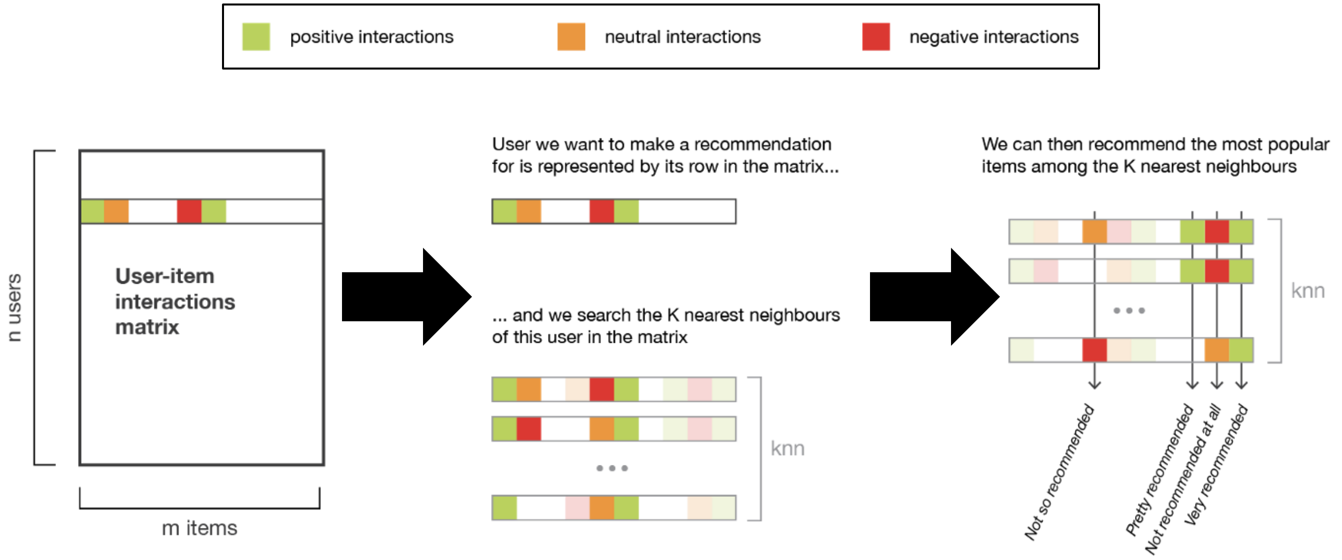
User-User



Solution 1: Nearest User (User-User)

User-User Recommendation:

- Given a user u_i, compute their k nearest neighbors.
- Recommend the items that are most popular amongst the nearest neighbors.



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Group

2 min

- What do you see as pros / cons of the nearest user approach to recommendations?

Solution 1 (User-User) Pros / Cons

Pros:

- Personalized to the user.

Cons:

- Nearest Neighbors might be too similar
  - This approach only works if the nearest neighbors have interacted with items that the user hasn't.
- Feedback Loop (Echo Chambers)
- Scalability
  - Must store and search through entire user-item matrix
- Cold-Start Problem
  - What do you do about new users, with no data?

Solution 2: “People Who Bought This Also Bought…”

Item-Item

Solution 2: “People Who Bought This Also Bought…” (Item-Item)

Item-Item Recommendation:

- Create a **co-occurrence matrix** $C \in \mathbb{R}^{m \times m}$ (m is the number of items). C_{ij} = # of users who bought both item i and j.
- For item i, predict the top-k items that are bought together.

	Sunglasses	Baby Bottle	…	Diapers	Swim Trunks	Baby Formula
Sunglasses	500	15	…	9	130	20
Baby Bottle	15	45	…	6	10	10
…	…	…	…	…	…	…
Diapers	9	6	…	30	9	6
Swim Trunks	130	10	…	9	200	8
Baby Formula	20	10	…	6	8	50

Normalizing Co-Occurence Matrices

Problem: popular items drown out the rest!

Solution: Normalizing using Jaccard Similarity.

$$S_{ij} = \frac{\#\text{ purchased } i \textbf{ and } j}{\#\text{ purchased } i \textbf{ or } j} = \frac{C_{ij}}{C_{ii} + C_{jj} - C_{ij}}$$

	Sunglasses	Baby Bottle	...	Diapers	Swim Trunks	Baby Formula
Sunglasses	1.00	0.03	...	0.02	0.23	0.04
Baby Bottle	0.03	1.00	...	0.09	0.04	0.12
...	...	...	...	...	...	...
Diapers	0.02	0.09	...	1.00	0.04	0.08
Swim Trunks	0.23	0.04	...	0.04	1.00	0.03
Baby Formula	0.04	0.12	...	0.08	0.03	1.00

Incorporating Purchase History

What if I know the user u has bought a baby bottle and formula?

Idea: Take the average similarity between items they have bought

$$Score(u, diapers) = \frac{S_{diapers,baby\ bottle} + S_{diapers,baby\ formula}}{2}$$

Could also weight them differently based on recency of purchase!

Then all we need to do is find the item with the highest average score!

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Group

2 min

- What do you see as pros / cons of the item-item approach to recommendations?

Solution 2 (Item-Item) Pros / Cons

Pros:

- Personalizes to item (incorporating purchase history also personalizes to the user)

Cons:

- Can still suffer from feedback loops
  - (As can all recommender systems – but in some cases it's worse than others)
- Scalability (must store entire item-item matrix)
- Cold-Start Problem
  - What do you do about new ***items***, with no data?

Solution 3: Feature-Based

Solution 3: Feature-Based

What if we know what factors lead users to like an item?

Idea: Create a feature vector for each item. Learn a regression model!

Genre	**Year**	**Director**	**...**
Action	1994	Quentin Tarantino	...
Sci-Fi	1977	George Lucas	...

Define weights on these features for **all users** (global)

$$w_G \in \mathbb{R}^d$$

Fit linear model

Solution 3: Feature-Based

What if we know what factors lead users to like an item?

Idea: Create a feature vector for each item. Learn a regression model!

Genre	Year	Director	...
Action	1994	Quentin Tarantino	...
Sci-Fi	1977	George Lucas	...

Define weights on these features for **all users** (global)

$$w_G \in \mathbb{R}^d$$

Fit linear model

$$\hat{r}_{uv} = w_G^T h(v) = \sum_i w_{G,i}\, h_i(v)$$

$$\hat{w}_G = argmin_w \frac{1}{\#\, ratings} \sum_{u,v:r_{uv} \neq ?} (w_G^T h(v) - r_{uv})^2 + \lambda \|w_G\|$$

Personalization: Option A

Add user-specific features to the feature vector!

Genre	Year	Director	...	Gender	Age	...
Action	1994	Quentin Tarantino	...	F	25	...
Sci-Fi	1977	George Lucas	...	M	42	...

Personalization: Option B

Include a user-specified deviation from the global model.

$$\hat{r}_{uv} = (\widehat{w}_G + \widehat{w}_u)^T h(v)$$

Start a new user at $\widehat{w}_u = 0$, update over time.

- OLS on the residuals of the global model
- Bayesian Update (start with a probability distribution over user-specific deviations, update as you get more data)

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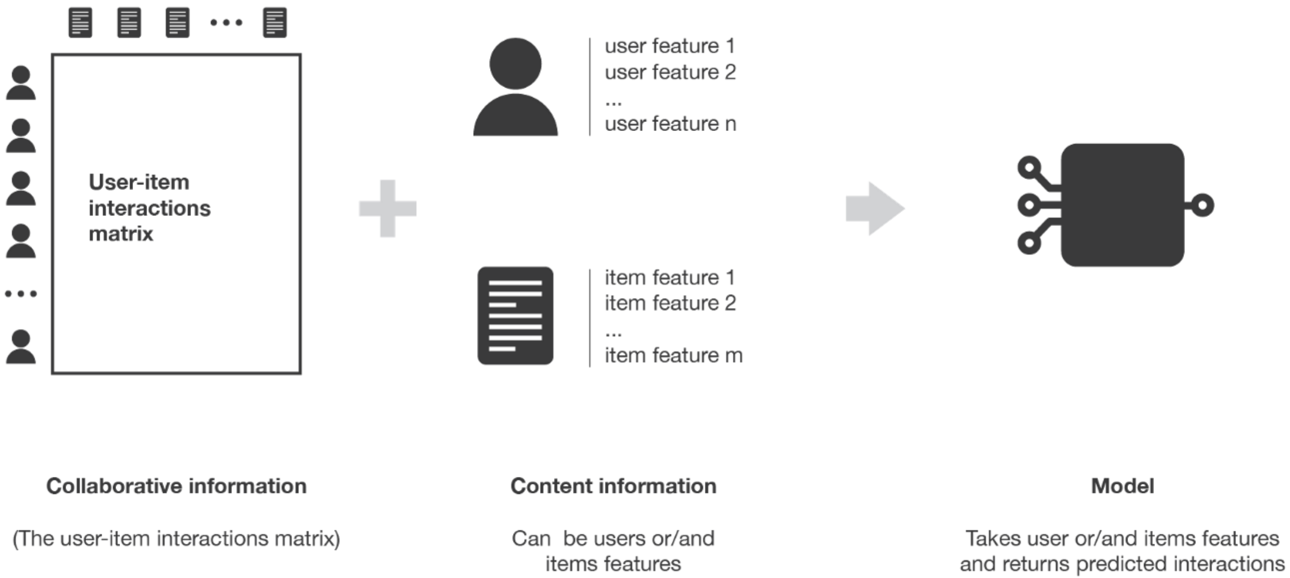
Group

2 min

- Will feature-based recommender systems suffer from the cold start problem? Why or why not?
- What about other pros/cons of feature-based?



Solution 3 (Feature-Based) Pros / Cons

Pros:

- No cold-start issue!
  - Even if a new user/item has no purchase history, you know features about them.
- Personalizes to the user and item.
- Scalable (only need to store weights per feature)
- Can add arbitrary features (e.g., time of day)

Cons:

- Hand-crafting features is very tedious and unscalable ☹

Recap

Dimensionality Reduction & PCA:

- Why and when it's important
- High level intuition for PCA
- Linear Projections & Reconstruction
- Eigenvectors / Eigenvalues

Recommender Systems:

- Sol 0: Popularity
- Sol 1: Nearest User (User-User)
- Sol 2: "People who bought this also bought" (item-item)
- Sol 3: Feature-Base

Next Time (Rec System Continued):

- Sol 4: Matrix Factorization
- Sol 5: Hybrid Model
- Addressing common issues with Recommender Systems
- Evaluating Recommender Systems