Recommender Systems

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Recommender systems

- We will discuss one of the most popular applications of data science
  - Recommender Systems
- Every website does it
- Recommender Systems match users with items
- Users under constant information overload
- Think songs, foods, drinks, movies, news

Examples

- This is even done offline in the service industry!
- Can you think of other examples?

Collaborative filtering

- Collaborative filtering is an effort to predict how products/items will be rated by a user, given previous ratings (from both the user and others)
- This prediction can help us recommend to the user only items that we think she will rate highly
- Latent Factor Models - Netflix Challenge (1M$)- Simon Funk

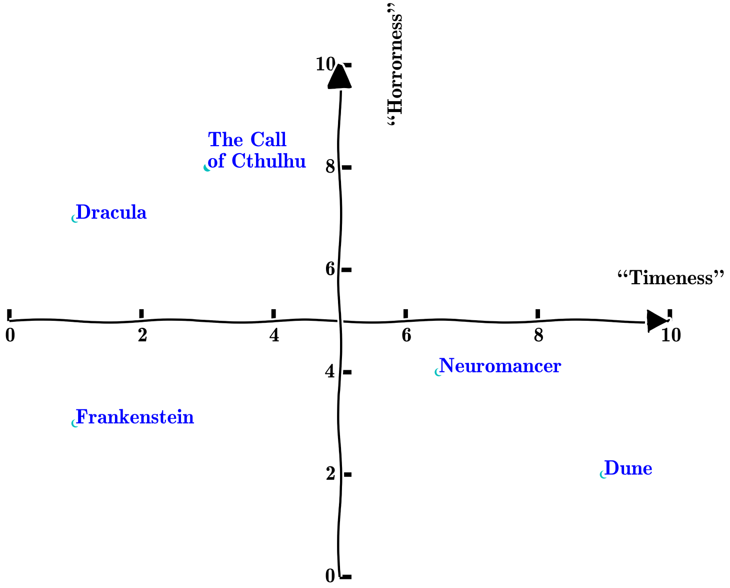
Same sample data

	The Call of Cthulhu	Frankenstein	Dracula	Neuromancer	Dune
0	6	0	0	7	NaN
1	5	0	5	6	5
2	9	NaN	4	NaN	8
3	4	NaN	2	5	6
4	4	NaN	4	6	0
5	6	3	8	5	7
6	NaN	6	NaN	6	7
7	NaN	1	1	6	NaN
8	NaN	NaN	2	NaN	9
9	NaN	3	4	5	7

Factors

- We are going to base our predictions on “hidden” qualities of the items
- For example, food can have different levels of spiciness, a drink different levels of bitterness
- We term these qualities “factors”
- A sensible way of describing items would be to see them as a collection of “factors”
  - But our data is just ratings!
- Thus, our factors are “latent”, i.e. hidden!

Example factors for our data



Factors and user preferences

- Let's assume n factors
- We can encode factors as a real valued vector $\boldsymbol{item\_factors_i} = [\phi_0, \phi_1, ..., \phi_{n-1}]$
- For example "The Call of the Cthulhu" can be encoded as $\boldsymbol{item\_factors_0} = [3, 8]$
- Each user now can have preferences over factors, encoded as weights $\boldsymbol{user\_preferences_j} = [w_0, w_1, ..., w_{n-1}]$
- The weight vector contains user preferences, e.g. $\boldsymbol{user\_preferences_0} = [0.5, 0.8]$
- But we don't have any user weights nor any item factors - generate some random!

Some random data

- Each row in $\boldsymbol{user\_preferences}$ represents the preferences of a user, while each row in $\boldsymbol{item\_factors}$ represents the factors of an item

```
array([[ 0.092,  0.783],
       [ 0.78 ,  0.488],
       [ 0.844,  0.062],
       [ 0.68 ,  0.549],
       [ 0.212,  0.43 ],
       [ 0.961,  0.023],
       [ 0.659,  0.31 ],
       [ 0.92 ,  0.769],
       [ 0.817,  0.452],
       [ 0.834,  0.887]])
```

```
array([[ 0.338,  0.519],
       [ 0.69 ,  0.256],
       [ 0.363,  0.93],
       [ 0.004,  0.112],
       [ 0.608,  0.104]])
```

$$rating[0][0] \leftarrow 0.437 = 0.092 * 0.338 + 0.783 * 0.519$$

Far away from the observed rating of 6

Predict ratings

- Example python code
- Still random values...

```
def predict_rating(user_row,item_row):
    """ Predict a rating given a user_row and an item_row.
    """
    user_values = user_preferences[user_row]
    item_values = item_factors[item_row]
    return user_values.dot(item_values)
```

Training for a single example

- $\boldsymbol{user\_preferences}$ and $\boldsymbol{item\_factors}$ have random values!
- Find the difference between the real and the predicted rating ("how far away am I from the goal ?")
- Multiply by small learning rate $\alpha = 0.0001$ ("Don't take my measurement so seriously")
- Move $\boldsymbol{user\_preferences}$ and $\boldsymbol{item\_factors}$ towards the correct value, following the negative of the gradient ("Let's move towards the direction of the most abrupt change")

Training code

```
def train(user_row,item_row,rating,alpha = 0.0001):
    """ Adapt the values of user_preferences and item_factors
        to match the ones predicted by the users
    """
    err = alpha * (rating - predict_rating(user_row, item_row))
    user_preferences[user_row] += err * item_factors[item_row]
    item_factors[item_row] += err * user_preferences[user_row]
```

Training using all data

- "Latent Factors" because we have never really observed them, we can only infer them
- Loop over all $\boldsymbol{user\_preferences}$ and $\boldsymbol{item\_factors}$
- Ignore cells with no value ("NaN" cells)
- Repeat until some criterion (in our case, 30,000 iterations)

Training using all data code

```
def sgd_svd(iterations = 30000):
    """ Iterate over all users and all items and train for
        a certain number of iterations
    """
    for i in range(0,iterations):
        for user_row in range(0,user_preferences.shape[0]):
            for item_row in range(0,item_factors.shape[0]):
                rating = user_ratings[user_row][item_row]
                if(not np.isnan(rating)):
                    train(user_row,item_row,rating)
```

Reconstructing data / predicting unseen ratings

- Run *sgd_svd*() and print the updated tables

```
array([[ 1.705,  0.486],
       [ 1.857,  0.484],
       [ 2.373,  1.311],
       [ 0.988,  1.495],
       [ 2.519, -2.088],
       [ 1.868,  1.235],
       [ 1.367,  1.801],
       [ 1.405,  0.628],
       [ 0.133,  3.453],
       [ 1.562,  1.235]]
```

```
array([[ 2.713,  1.266],
       [-1.125,  4.09 ],
       [ 1.847,  0.514],
       [ 3.09 ,  0.807],
       [ 2.079,  2.522]])
```

$rating[0][0] \leftarrow 1.705 * 2.713 + 0.486 * 1.266 \approx 5.2$, not 6, but close!

Visual comparison

- Calculate all predicted values and pretty print

	The Call of Cthulhu	Frankenstein	Dracula	Neuromancer	Dune
0	(6.000|5.209)	(0.000|0.029)	(0.000|3.397)	(7.000|5.699)	(nan|4.587)
1	(5.000|5.662)	(0.000|-0.046)	(5.000|3.699)	(6.000|6.208)	(5.000|4.956)
2	(9.000|8.112)	(nan|2.705)	(4.000|5.098)	(nan|8.443)	(8.000|8.198)
3	(4.000|4.564)	(nan|4.518)	(2.000|2.651)	(5.000|4.262)	(6.000|5.799)
4	(4.000|4.214)	(nan|-9.302)	(4.000|3.425)	(6.000|6.127)	(0.000|0.017)
5	(6.000|6.617)	(3.000|3.004)	(8.000|4.100)	(5.000|6.756)	(7.000|7.003)
6	(nan|5.960)	(6.000|5.735)	(nan|3.473)	(6.000|5.593)	(7.000|7.508)
7	(nan|4.577)	(1.000|0.950)	(1.000|2.918)	(6.000|4.858)	(nan|4.397)
8	(nan|4.494)	(nan|12.716)	(2.000|2.010)	(nan|2.851)	(9.000|8.985)
9	(nan|5.769)	(3.000|3.336)	(4.000|3.523)	(5.000|5.774)	(7.000|6.389)

- For user 2, recommend “Neuromancer” and ignore “Frankenstein”
- Observe how reconstruction is not perfect - multiple reasons (e.g. data shuffling? mini-batches? more factors? more training)

Other outcome signals

- We have used ratings
- But this is not the only possible outcome
- One can use other signals as well
    - User have searched for certain films
    - Users have clicked on certain films

How about adding known factors/features?

- Until now we only had latent factors
- But latent factors arise only when you actually have some a good number of $ pairs for a user
  - What if the user just joined the website?
- What if you don't have any?
  - Or what if you have further observations about a user

Item descriptions

- Instead of based only on latent factors, we can base our predictions on known observations
- For example each book can have:
  - Genre
  - Data published
  - Age of intended audience
  - Author
- Each film can have
  - Genre
  - Director
  - Age of intended audience

User descriptions

- But we might have data collected about a user as well
  - Age
  - Sex
  - Country of birth
  - Native language
- All kinds of data

Explicit knowledge

- You ask the user questions explicitly
  - What kind of books do you like?
  - What is the maximum price you would pay for a book?

Content based filtering

- One can use all features defined on the user and the item
- Create a classifier and do the predictions using the classifier
- We have very few samples
  - So we are going to use a linear classifier

Item feature matrix

Feature 0: First critic score of the book

Feature 1: Second critic score of the book

	Critic0	Critic1
0	0.3	0.9
1	0.9	0.3
2	0.6	0.4
3	0.2	0.1
4	0.7	0.8
5	0.9	0.1

User feature matrix

Feature 0: Male/Female

Feature 1: Over 60

	Sex	Over60
0	1.0	0.0
1	0.0	1.0
2	0.0	0.0
3	1.0	0.0
4	0.0	1.0
5	0.0	0.0
6	0.0	0.0
7	1.0	0.0
8	0.0	1.0
9	1.0	0.0

Combining the features

- We need to build a set of features for training for each person/item combo

	Sex	Over60	key	user_id	Critic0	Critic1	item_id	rating
0	1.0	0.0	0	0	0.3	0.9	0	8.0
1	1.0	0.0	0	0	0.9	0.3	1	2.0
3	1.0	0.0	0	0	0.2	0.1	3	5.0
4	1.0	0.0	0	0	0.7	0.8	4	4.0
0	0.0	1.0	0	1	0.3	0.9	0	3.0
1	0.0	1.0	0	1	0.9	0.3	1	2.0
3	0.0	1.0	0	1	0.2	0.1	3	7.0
4	0.0	1.0	0	1	0.7	0.8	4	7.0
0	0.0	0.0	0	2	0.3	0.9	0	9.0
2	0.0	0.0	0	2	0.6	0.4	2	7.0
3	0.0	0.0	0	2	0.2	0.1	3	8.0
4	0.0	0.0	0	2	0.7	0.8	4	5.0
2	1.0	0.0	0	3	0.6	0.4	2	7.0
3	1.0	0.0	0	3	0.2	0.1	3	8.0
4	1.0	0.0	0	3	0.7	0.8	4	9.0
1	0.0	1.0	0	4	0.9	0.3	1	1.0
2	0.0	1.0	0	4	0.6	0.4	2	8.0
3	0.0	1.0	0	4	0.2	0.1	3	3.0

Test set

- We are looking to predict this:

	Sex	Over60	key	user_id	Critic0	Critic1	item_id	rating
2	1.0	0.0	0	0	0.6	0.4	2	NaN
2	0.0	1.0	0	1	0.6	0.4	2	NaN
1	0.0	0.0	0	2	0.9	0.3	1	NaN
0	1.0	0.0	0	3	0.3	0.9	0	NaN
1	1.0	0.0	0	3	0.9	0.3	1	NaN
0	0.0	1.0	0	4	0.3	0.9	0	NaN
3	0.0	0.0	0	5	0.2	0.1	3	NaN
4	0.0	0.0	0	5	0.7	0.8	4	NaN
2	0.0	0.0	0	6	0.6	0.4	2	NaN
2	0.0	1.0	0	8	0.6	0.4	2	NaN
1	1.0	0.0	0	9	0.9	0.3	1	NaN

Code - Pandas magic!!!

```
user_ratings_df = pd.read_csv("user_ratings.csv")
user_features_df = pd.read_csv("user_features.csv")
item_features_df = pd.read_csv("item_features.csv")


user_features_df["key"] = 0
user_features_df["user_id"] = range(0,user_features_df.shape[0])
item_features_df["key"] = 0
item_features_df["item_id"] = range(0,item_features_df.shape[0])

merged_df = pd.merge(user_features_df, item_features_df,left_index=True,on="key")




merged_df["rating"] = map(lambda ids: user_ratings_df.values[ids[1]][ids[2]],
                          merged[["user_id", "item_id"]].itertuples())

train = merged_df.dropna()

test = merged_df[merged.isnull().any(axis=1)]
```

Hybrid systems

- Can we merge the two approaches?
  - Of course we can - various ways of merging
- We will just augment collaborative filtering with standard features for now
- We can add the features as parts of the variables we are going to learn

Regularisation

- We will now add a penalty to features depending on what they are
- Penalty strong for latent features
- But could be the other way around
- Weight decays / l_2 regulariser
  - $w_i = w_i - \alpha(y_p - y)(\phi_i + \lambda w_i)$

Code - predict

```python
def predict_rating(user_id,item_id):
    """ Predict a rating given a user_id and an item_id.
    """
    user_preference = latent_user_preferences[user_id]
    item_preference = latent_item_features[item_id]

    user_score = user_features_weights[user_id].dot(user_features[user_id])
    item_score = item_features_weights[item_id].dot(item_features[item_id])

    return user_preference.dot(item_preference) + user_score + item_score
```

Code - train

```
def train(user_id, item_id, rating,alpha = 0.0001,
                                   latent_feature_weight_decay = 0.1,
                                   user_weight_decay = 0.01,
                                   item_weight_decay = 0.001):


    prediction_rating = predict_rating(user_id, item_id)
    err =  ( prediction_rating - rating );

    user_pref_values = latent_user_preferences[user_id][:]
    latent_user_preferences[user_id] -= alpha *
                                        err *  ( latent_item_features[item_id] +
                                                 latent_feature_weight_decay*
                                                 latent_user_preferences[user_id])
    latent_item_features[item_id] -= alpha *
                                     err * ( user_pref_values +
                                     latent_feature_weight_decay*latent_item_features[item_id])

    user_features_weights[user_id] -=alpha * err *(  user_features[user_id] +
                                                     user_weight_decay* user_features_weights[user_id])
    item_features_weights[item_id] -=alpha * err * ( item_features_weights[item_id] +
                                                     item_weight_decay* item_features_weights[item_id])


    return err
```

Removing latent factors

- What will happen to the example above if we remove all latent factors?
  - ... and base our decisions only in known features
- Factors vs features

Evaluating

- Cross-validation again!
- We have used all the data in our examples
  - Is this correct?
- What would be the proper way of evaluating the system?

Implicit feedback

- How about cases where you
- When you are recommending books or food user preferences user likes/dislikes something
- How about if you are recommending
  - News?
  - Adverts?
- You are limited to clicks!
- But they are not proper feedback
  - User might not have seen something

No negative feedback regimes

- Not clicking is not negative feedback
- Create a preference matrix - 1 if user has clicked, 0 if she hasn't
- Weight the importance of each example by $c(i, j) = 1 + \alpha r(i, j)$
  - $r(i, u)$ is the number of clicks

Contextual bandits

- You can personalise the above scenario even further
- Send the user some random examples (e.g. news)
  - With let's say 0.2 probability
- Seems familiar?
- Obviously better solutions than ϵ-greedy

Conclusion

- We have seen various instances of recommender systems
- Again, there are far more complex models
- But the examples here should have given you a good view about what is out there
- Also, pandas
  - Bring your data to a format that is usable by relevant libraries!