Movie_Similarity_Model

December 14, 2016

In [1]:
```
import heapq
import math
import time
from collections import defaultdict
from collections import namedtuple
from contextlib import contextmanager
from datetime import datetime

import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from sklearn.metrics import mean_squared_error
from sklearn.metrics import r2_score
from sklearn.model_selection import train_test_split

%matplotlib inline
```

In [5]:
```
@contextmanager
def elapsed_time(title):
    start = time.time()
    yield
    elapsed = time.time() - start
    print '%s: %.2f secs' % (title, elapsed)


def get_xy(ratings_df):
    y = ratings_df['rating']
    x = ratings_df.drop('rating', axis=1)
    return x, y


def root_mean_squared_error(y, y_pred):
    return math.sqrt(mean_squared_error(y, y_pred))


def show_scores_plot(k_neighbors_values, val_scores, train_scores, model_na
    _, ax = plt.subplots(1, 1, figsize=(15, 10))
```

```
    ax.plot(k_neighbors_values, val_scores, label='validation')
    ax.plot(k_neighbors_values, train_scores, label='train')

    ax.set_xlabel('k_neighbors')
    ax.set_ylabel('$R^2$')
    ax.set_title('Test and validation scores for different k_neighbors valu

    ax.legend(loc='best')

    plt.tight_layout()
    plt.show()


def score_model(ratings_df, model_f, model_name):
    train_val_ratings_df, test_ratings_df = train_test_split(ratings_df)

    train_ratings_df, validation_ratings_df = train_test_split(train_val_ra

    best_score = -float('inf')
    best_k_neighbors = None

    model = model_f()

    model = model.fit(train_ratings_df)

    k_neighbors_values = [1, 5, 10, 20, 30, 40, 50, 60, 80, 100]

    val_scores = []
    train_scores = []

    for k_neighbors in k_neighbors_values:
        model.set_k_neighbors(k_neighbors=k_neighbors)

        x_train, y_train = get_xy(train_ratings_df)
        x_val, y_val = get_xy(validation_ratings_df)

        y_train_pred = model.predict(x_train)
        y_val_pred = model.predict(x_val)

        train_score = r2_score(y_train, y_train_pred)
        val_score = r2_score(y_val, y_val_pred)

        if val_score > best_score:
            best_score = val_score
            best_k_neighbors = k_neighbors

        val_scores.append(val_score)
```

```
            train_scores.append(train_score)

            print 'k: %d, validation score: %.5f, train score: %.5f\n' % (k_nei

        print 'best k: %d, best score: %.5f' % (best_k_neighbors, best_score)

        model = model_f(k_neighbors=best_k_neighbors)

        model = model.fit(train_val_ratings_df)

        x_train_val, y_train_val = get_xy(train_val_ratings_df)
        x_test, y_test = get_xy(test_ratings_df)

        y_train_val_pred = model.predict(x_train_val)
        y_test_pred = model.predict(x_test)

        train_val_score = r2_score(y_train_val, y_train_val_pred)
        test_score = r2_score(y_test, y_test_pred)

        train_val_rmse = root_mean_squared_error(y_train_val, y_train_val_pred)
        test_rmse = root_mean_squared_error(y_test, y_test_pred)

        print 'train score: %.4f, test score: %.4f' % (train_val_score, test_sc
        print 'train rmse: %.4f, test rmse: %.4f' % (train_val_rmse, test_rmse)

        show_scores_plot(k_neighbors_values, val_scores, train_scores, model_na
```

```
In [6]: def date_parse(time_in_secs):
            return datetime.utcfromtimestamp(float(time_in_secs))


        def read_ratings_df_with_timestamp(file_name):
            with elapsed_time('loaded csv'):
                ratings_df = pd.read_csv(file_name, parse_dates=['timestamp'], date
            return ratings_df
```

```
In [7]: class BaselineModel(object):
            def predict_rating(self, user_id, movie_id):
                pass

            def predict(self, x):
                return [self.predict_rating(row['userId'], row['movieId']) for _, r

            def score(self, x, y):
                return r2_score(y, self.predict(x))


        class BaselineEffectsModel(BaselineModel):
```

```
def __init__(self, movie_lambda=5.0, user_lambda=20.0):
    self.movie_lambda = movie_lambda
    self.user_lambda = user_lambda

    self.y_mean = None
    self.movie_effects = None
    self.user_effects = None
    self.user_groups = None

def calculate_movie_effect(self, ratings):
    return (ratings - self.y_mean).sum() / (self.movie_lambda + len(rat

def calculate_movie_effects(self, movie_ratings):
    return movie_ratings.agg(lambda ratings: self.calculate_movie_effec

def calculate_user_effect(self, ratings_df):
    s = 0.0
    for _, row in ratings_df.iterrows():
        s += row['rating'] - self.y_mean - self.movie_effects[row['movi

    return s / (self.user_lambda + len(ratings_df))

def calculate_user_effects(self, user_groups):
    user_ids = []
    user_effects = []

    for user_id, group in user_groups:
        user_effect = self.calculate_user_effect(group)

        user_ids.append(user_id)
        user_effects.append(user_effect)

    return pd.Series(user_effects, index=user_ids)

def fit(self, ratings_df):
    with elapsed_time('effects init'):
        _, y_train = get_xy(ratings_df)
        self.y_mean = y_train.mean()

        movie_ratings = ratings_df.groupby('movieId')['rating']
        self.user_groups = ratings_df.groupby('userId')

        self.movie_effects = self.calculate_movie_effects(movie_ratings
        self.user_effects = self.calculate_user_effects(self.user_grou

    return self

def create_modified_ratings(self, ratings_df):
```

```
        ratings_df = ratings_df.copy()

        for index, row in ratings_df.iterrows():
            user_id = row['userId']
            movie_id = row['movieId']
            rating = row['rating']
            pred_rating = self.predict_baseline_rating(user_id, movie_id)

            residual = rating - pred_rating

            ratings_df.loc[index, 'rating'] = residual

        return ratings_df

    def predict_baseline_rating(self, user_id, movie_id):
        return self.y_mean + self.movie_effects.get(movie_id, 0.0) + self.u

    def predict_rating(self, user_id, movie_id):
        return self.predict_baseline_rating(user_id, movie_id)
```

Movie similarity model.

First we removed all main global effects the same way we did for our baseline model. We subtracted the total rating mean, then we removed the movie effects and then user effects.

As a result our utility matrix was the residuals after applying the baseline model.

It allowed us to remove some scale differences in the way different users rate movies.

In our movie similarity model we predict the rating for a movie (movie_id) and a user (user_id) by

1) finding k closest neighbors (k=40,50)

For assessing item-item similarity we used a distance based on the mean squared error between items [1]:

$s_{ij} = \frac{|U(i,j)|}{\sum_{u \in U(i,j)} (r_{ui} - r_{uj})^2 + \alpha}$, where U(i,j) is the set of users who rated both items j and k.

2) since relatively large number of movies have low number of ratings (1-3), some of the movies have zero neighbors, in this case we use a baseline prediction (in 6.9-7.2% of the cases for the test set).

[1] R.Bell, Y.Koren, "Improved Neighborhood-based Collaborative Filtering", *KDD-Cup and Workshop*, ACM press, 2007

```
In [8]: MovieSimilarity = namedtuple('MovieSimilarity', ['movie_id', 'similarity'])


        class MovieSimilarityModel(BaselineModel):
            def __init__(self, k_neighbors=40):
                self.k_neighbors = k_neighbors

                self.baseline_model = BaselineEffectsModel()
```

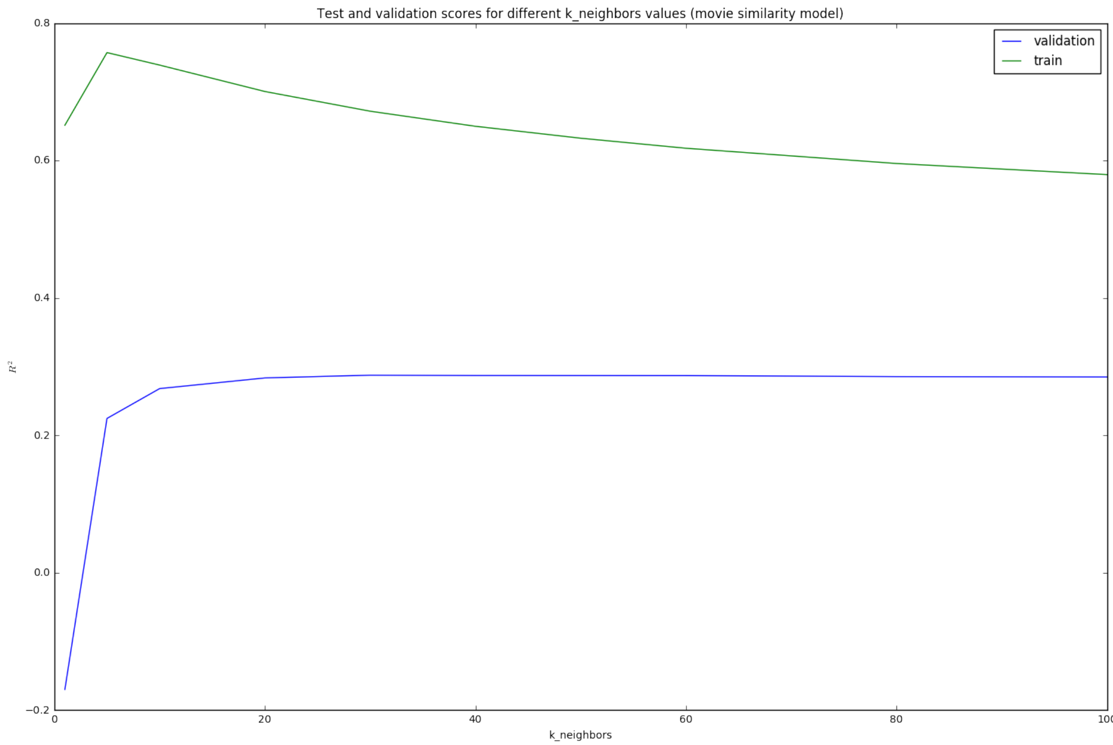
```
        self.ratings_by_movie = defaultdict(dict)
        self.ratings_by_user = defaultdict(dict)
        self.raters_by_movie = {}
        self.movie_similarity = {}
        # self.movie_aij = {}

    def set_k_neighbors(self, k_neighbors):
        self.k_neighbors = k_neighbors

    def calculate_common_raters(self, movie_id_1, movie_id_2):
        raters1 = self.raters_by_movie[movie_id_1]
        raters2 = self.raters_by_movie[movie_id_2]
        return raters1 & raters2

    def get_common_ratings(self, movie_id, raters):
        all_ratings = self.ratings_by_movie[movie_id]
        ratings = []
        for rater_id in raters:
            ratings.append(all_ratings[rater_id])

        return np.array(ratings)

    def calculate_similarity(self, movie_id_1, movie_id_2):
        common_raters = self.calculate_common_raters(movie_id_1, movie_id_2
        support = len(common_raters)
        if support <= 1:
            similarity = 0.0
            # aij = 0.0
        else:
            ratings1 = self.get_common_ratings(movie_id_1, common_raters)
            ratings2 = self.get_common_ratings(movie_id_2, common_raters)

            alpha = 4.0

            similarity = support / (np.power(ratings1 - ratings2, 2).sum()

            # aij = np.multiply(ratings1, ratings2).sum() / support

        return similarity

    def fit(self, ratings_df):
        with elapsed_time('fit'):
            self.baseline_model.fit(ratings_df)

            ratings_df = self.baseline_model.create_modified_ratings(rating

            unique_movie_ids = np.array(sorted(ratings_df['movieId'].unique
```

```
            for _, row in ratings_df.iterrows():
                movie_id = row['movieId']
                user_id = row['userId']
                rating = row['rating']
                self.ratings_by_movie[movie_id][user_id] = rating
                self.ratings_by_user[user_id][movie_id] = rating

            for movie_id in unique_movie_ids:
                self.raters_by_movie[movie_id] = set(self.ratings_by_movie[

            for movie_index_1, movie_id_1 in enumerate(unique_movie_ids):
                for movie_index_2 in xrange(movie_index_1 + 1, len(unique_m
                    movie_id_2 = unique_movie_ids[movie_index_2]

                    similarity = self.calculate_similarity(movie_id_1, movi
                    movie_pair = (movie_id_1, movie_id_2)
                    self.movie_similarity[movie_pair] = similarity
                    # self.movie_aij[movie_pair] = aij

        return self

    def get_similarity(self, movie_id_1, movie_id_2):
        if movie_id_1 < movie_id_2:
            id_1 = movie_id_1
            id_2 = movie_id_2
        else:
            id_1 = movie_id_2
            id_2 = movie_id_1

        return self.movie_similarity.get((id_1, id_2), -1.0)

    def clear_predict_caches(self):
        self.zero_prediction_count = 0

    def predict_rating(self, user_id, movie_id):
        ratings = self.ratings_by_user[user_id]

        elements = []

        for movie_id_2 in ratings:
            if movie_id != movie_id_2:
                similarity = self.get_similarity(movie_id, movie_id_2)
                if similarity > 0.0:
                    elements.append(MovieSimilarity(movie_id_2, similarity)

        movie_similarities = heapq.nlargest(self.k_neighbors, elements, key

        if len(movie_similarities) > 0:
```

```
                similarity_sum = 0.0
                product_sum = 0.0
                for movie_similarity in movie_similarities:
                    movie_id_2 = movie_similarity.movie_id
                    rating = ratings[movie_id_2]
                    similarity = movie_similarity.similarity

                    product_sum += similarity * rating
                    similarity_sum += similarity

                rating = product_sum / similarity_sum
            else:
                rating = 0.0
                self.zero_prediction_count += 1

            result = self.baseline_model.predict_baseline_rating(user_id, movie

            return result

        def predict(self, x):
            self.clear_predict_caches()
            predictions = [self.predict_rating(row['userId'], row['movieId']) f
            print 'used baseline predictions: %.1f%%' % (100.0 * self.zero_pred
            return predictions


    ratings_df = read_ratings_df_with_timestamp('ml-latest-small/ratings.csv')

    with elapsed_time('score model'):
        score_model(ratings_df, model_f=MovieSimilarityModel, model_name='movie
```

```
loaded csv: 0.13 secs
effects init: 5.18 secs
fit: 81.15 secs
used baseline predictions: 4.9%
used baseline predictions: 9.1%
k: 1, validation score: -0.16982, train score: 0.65154

used baseline predictions: 4.9%
used baseline predictions: 9.1%
k: 5, validation score: 0.22471, train score: 0.75729

used baseline predictions: 4.9%
used baseline predictions: 9.1%
k: 10, validation score: 0.26815, train score: 0.73911

used baseline predictions: 4.9%
used baseline predictions: 9.1%
```

```
k: 20, validation score: 0.28365, train score: 0.70066

used baseline predictions: 4.9%
used baseline predictions: 9.1%
k: 30, validation score: 0.28770, train score: 0.67197

used baseline predictions: 4.9%
used baseline predictions: 9.1%
k: 40, validation score: 0.28723, train score: 0.65002

used baseline predictions: 4.9%
used baseline predictions: 9.1%
k: 50, validation score: 0.28714, train score: 0.63265

used baseline predictions: 4.9%
used baseline predictions: 9.1%
k: 60, validation score: 0.28707, train score: 0.61805

used baseline predictions: 4.9%
used baseline predictions: 9.1%
k: 80, validation score: 0.28558, train score: 0.59584

used baseline predictions: 4.9%
used baseline predictions: 9.1%
k: 100, validation score: 0.28510, train score: 0.57967

best k: 30, best score: 0.28770
effects init: 6.42 secs
fit: 118.84 secs
used baseline predictions: 3.9%
used baseline predictions: 7.0%
train score: 0.6879, test score: 0.3045
train rmse: 0.5921, test rmse: 0.8776
```




```
score model: 663.38 secs
```

```
In [9]: UserSimilarity = namedtuple('UserSimilarity', ['user_id', 'similarity'])


        class UserSimilarityModel(BaselineModel):
            def __init__(self, k_neighbors=40):
                self.k_neighbors = k_neighbors

                self.baseline_model = BaselineEffectsModel()
                self.ratings_by_movie = defaultdict(dict)
                self.ratings_by_user = defaultdict(dict)
                self.movies_by_user = {}
                self.user_similarity = {}

            def set_k_neighbors(self, k_neighbors):
                self.k_neighbors = k_neighbors

            def calculate_common_movies(self, user_id_1, user_id_2):
                movies1 = self.movies_by_user[user_id_1]
                movies2 = self.movies_by_user[user_id_2]
                return movies1 & movies2
```

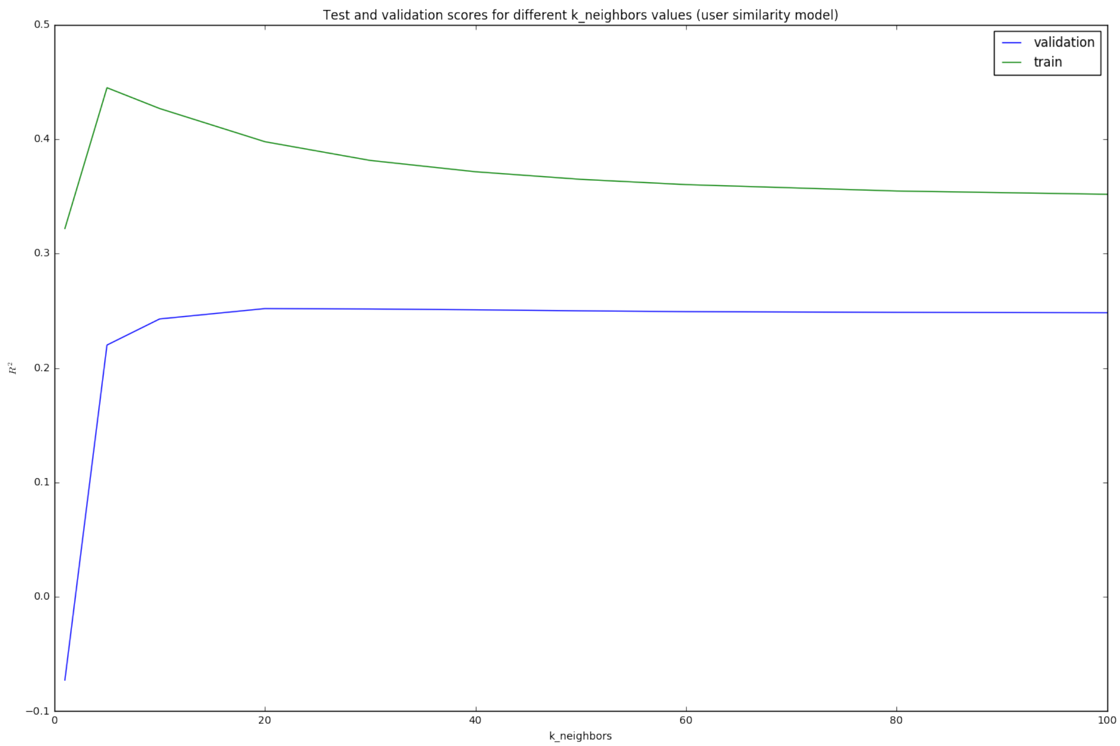
```
def get_common_ratings(self, user_id, movies):
    all_ratings = self.ratings_by_user[user_id]
    ratings = []
    for movie_id in movies:
        ratings.append(all_ratings[movie_id])

    return np.array(ratings)

def calculate_similarity(self, user_id_1, user_id_2):
    common_movies = self.calculate_common_movies(user_id_1, user_id_2)
    support = len(common_movies)
    if support <= 1:
        similarity = 0.0
        # aij = 0.0
    else:
        ratings1 = self.get_common_ratings(user_id_1, common_movies)
        ratings2 = self.get_common_ratings(user_id_2, common_movies)

        alpha = 4.0

        similarity = support / (np.power(ratings1 - ratings2, 2).sum()

    return similarity

def fit(self, ratings_df):
    with elapsed_time('fit'):
        self.baseline_model.fit(ratings_df)

        ratings_df = self.baseline_model.create_modified_ratings(rating

        unique_user_ids = np.array(sorted(ratings_df['userId'].unique()

        for _, row in ratings_df.iterrows():
            movie_id = row['movieId']
            user_id = row['userId']
            rating = row['rating']
            self.ratings_by_movie[movie_id][user_id] = rating
            self.ratings_by_user[user_id][movie_id] = rating

        for user_id in unique_user_ids:
            self.movies_by_user[user_id] = set(self.ratings_by_user[use

        for user_index_1, user_id_1 in enumerate(unique_user_ids):
            for user_index_2 in xrange(user_index_1 + 1, len(unique_use
                user_id_2 = unique_user_ids[user_index_2]

                similarity = self.calculate_similarity(user_id_1, user_
                user_pair = (user_id_1, user_id_2)
```

```
                    self.user_similarity[user_pair] = similarity

        return self

    def get_similarity(self, user_id_1, user_id_2):
        if user_id_1 < user_id_2:
            id_1 = user_id_1
            id_2 = user_id_2
        else:
            id_1 = user_id_2
            id_2 = user_id_1

        return self.user_similarity.get((id_1, id_2), -1.0)

    def clear_predict_caches(self):
        self.zero_prediction_count = 0

    def predict_rating(self, user_id, movie_id):
        ratings = self.ratings_by_movie[movie_id]

        elements = []

        for user_id_2 in ratings:
            if user_id != user_id_2:
                similarity = self.get_similarity(user_id, user_id_2)
                if similarity > 0.0:
                    elements.append(UserSimilarity(user_id_2, similarity))

        user_similarities = heapq.nlargest(self.k_neighbors, elements, key=

        if len(user_similarities) > 0:
            similarity_sum = 0.0
            product_sum = 0.0
            for user_similarity in user_similarities:
                user_id_2 = user_similarity.user_id
                rating = ratings[user_id_2]
                similarity = user_similarity.similarity

                product_sum += similarity * rating
                similarity_sum += similarity

            rating = product_sum / similarity_sum
        else:
            rating = 0.0
            self.zero_prediction_count += 1

        result = self.baseline_model.predict_baseline_rating(user_id, movie
```

```
            return result

        def predict(self, x):
            self.clear_predict_caches()
            predictions = [self.predict_rating(row['userId'], row['movieId']) f
            print 'used baseline predictions: %.1f%%' % (100.0 * self.zero_pred
            return predictions


with elapsed_time('build model'):
    score_model(ratings_df, model_f=UserSimilarityModel, model_name='user s
```

```
effects init: 5.13 secs
fit: 43.29 secs
used baseline predictions: 4.9%
used baseline predictions: 5.0%
k: 1, validation score: -0.07280, train score: 0.32184

used baseline predictions: 4.9%
used baseline predictions: 5.0%
k: 5, validation score: 0.22003, train score: 0.44494

used baseline predictions: 4.9%
used baseline predictions: 5.0%
k: 10, validation score: 0.24284, train score: 0.42677

used baseline predictions: 4.9%
used baseline predictions: 5.0%
k: 20, validation score: 0.25189, train score: 0.39777

used baseline predictions: 4.9%
used baseline predictions: 5.0%
k: 30, validation score: 0.25155, train score: 0.38140

used baseline predictions: 4.9%
used baseline predictions: 5.0%
k: 40, validation score: 0.25084, train score: 0.37151

used baseline predictions: 4.9%
used baseline predictions: 5.0%
k: 50, validation score: 0.24993, train score: 0.36488

used baseline predictions: 4.9%
used baseline predictions: 5.0%
k: 60, validation score: 0.24924, train score: 0.36026

used baseline predictions: 4.9%
used baseline predictions: 5.0%
```

```
k: 80, validation score: 0.24859, train score: 0.35467

used baseline predictions: 4.9%
used baseline predictions: 5.0%
k: 100, validation score: 0.24828, train score: 0.35182

best k: 20, best score: 0.25189
effects init: 6.40 secs
fit: 62.81 secs
used baseline predictions: 3.9%
used baseline predictions: 3.6%
train score: 0.4023, test score: 0.2708
train rmse: 0.8189, test rmse: 0.9006
```




```
build model: 236.93 secs
```

In [ ]: