## Movie Recommend by Surprise with GridSearch

In this notebook, optimize hyperparameters of Surprise using GridSearchCV.

#### In [1]:

```
import sys
import random
from surprise import Dataset, Reader
from surprise import KNNBasic, SVD
from surprise import accuracy
from surprise.model_selection import train_test_split
from surprise.model selection import cross validate
from surprise.model selection import GridSearchCV
from surprise.dataset import DatasetAutoFolds
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import operator
import requests
from zipfile import ZipFile
```

## In [17]:

```
df = pd.read csv('/kaggle/input/movies-and-ratings-for-recommendation-system/rating
s.csv',
                          error_bad_lines=False,
                          warn bad lines=False,
                          skiprows=lambda i: i>0 and random.random() > 0.1)
df.columns=['user id','item id','rating','timestamp']
print(len(df))
```

#### 10043

/opt/conda/lib/python3.7/site-packages/IPython/core/interactiveshell.p y:3552: FutureWarning: The warn bad lines argument has been deprecated and will be removed in a future version.

```
exec(code_obj, self.user_global_ns, self.user_ns)
/opt/conda/lib/python3.7/site-packages/IPython/core/interactiveshell.p
y:3552: FutureWarning: The error bad lines argument has been deprecate
d and will be removed in a future version.
```

```
exec(code obj, self.user global ns, self.user ns)
```

```
In [3]:
```

```
reader = Reader(rating_scale=(1,5))
data = Dataset.load_from_df(df[['user_id','item_id','rating']], reader)
print(type(data))
<class 'surprise.dataset.DatasetAutoFolds'>
   # cross_validate
   # Run 5-fold cross-validation and print results.
   results = cross_validate(algo, data, measures=['RMSE', 'MAE'], cv=5, verbose
   =True)
   print(results)
```

# GridSearchCV - algo to best\_algo

## In [4]:

```
algo = KNNBasic
param_grid = { 'k': [5,10,15,20,50], 'min_k': [2,3,4,5] }
gs = GridSearchCV(algo, param_grid, cv=5)
gs.fit(data)
```

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```

#### In [5]:

```
print(gs.best params)
best_algo = KNNBasic(k=gs.best_params['rmse']['k'], min_k=gs.best_params['rmse']['m
in_k'])
print(best_algo.k, best_algo.min_k)
{'rmse': {'k': 15, 'min k': 5}, 'mae': {'k': 15, 'min k': 5}}
15 5
```

In [6]:

help(best\_algo)

```
Help on KNNBasic in module surprise.prediction algorithms.knns object:
class KNNBasic(SymmetricAlgo)
   KNNBasic(k=40, min_k=1, sim_options={'user_based': True}, verbose=
True, **kwargs)
    A basic collaborative filtering algorithm.
    The prediction :math: \hat{r} {ui} is set as:
    .. math::
        \hat{r}_{ui} = \frac{1}{r}
        \sum_{v \in N^k_i(u)} \text{sim}(u, v) \ r_{vi}
        {\sum\limits_{v \in N^k_i(u)} \text{sim}(u, v)}
    or
    .. math::
        \hat{r}_{ui} = \frac{1}{r}
        \sum_{j \in N^k_u(i)} \text{sim}(i, j) \cdot r_{uj}
        {\sum\limits_{j \in N^k_u(i)} \text{sim}(i, j)}
    depending on the ``user_based`` field of the ``sim_options`` param
eter.
    Args:
        k(int): The (max) number of neighbors to take into account for
            aggregation (see :ref:`this note <actual_k_note>`). Defaul
t is
            ``40``.
        min k(int): The minimum number of neighbors to take into accou
nt for
            aggregation. If there are not enough neighbors, the predic
tion is
            set to the global mean of all ratings. Default is ``1``.
        sim options(dict): A dictionary of options for the similarity
            measure. See :ref:`similarity measures configuration` for
accepted
            options.
        verbose(bool): Whether to print trace messages of bias estimat
ion,
            similarity, etc. Default is True.
    Method resolution order:
        KNNBasic
        SymmetricAlgo
        surprise.prediction_algorithms.algo_base.AlgoBase
        builtins.object
    Methods defined here:
    __init__(self, k=40, min_k=1, sim_options={'user_based': True}, ve
rbose=True, **kwargs)
        Initialize self. See help(type(self)) for accurate signature.
    estimate(self, u, i)
    fit(self, trainset)
```

```
Train an algorithm on a given training set.
        This method is called by every derived class as the first basi
c step
        for training an algorithm. It basically just initializes some
internal
        structures and set the self.trainset attribute.
        Args:
            trainset(:obj:`Trainset <surprise.Trainset>`) : A training
                set, as returned by the :meth:`folds
                <surprise.dataset.Dataset.folds>` method.
        Returns:
            self
    Methods inherited from SymmetricAlgo:
    switch(self, u stuff, i stuff)
        Return x_stuff and y_stuff depending on the user_based field.
    Methods inherited from surprise.prediction_algorithms.algo_base.Al
goBase:
    compute baselines(self)
        Compute users and items baselines.
        The way baselines are computed depends on the ``bsl_options``
parameter
        passed at the creation of the algorithm (see
        :ref:`baseline_estimates_configuration`).
        This method is only relevant for algorithms using :func:`Pears
on
        baseline similarty<surprise.similarities.pearson_baseline>` or
the
        :class:`BaselineOnly
        <surprise.prediction_algorithms.baseline_only.BaselineOnly>` a
lgorithm.
        Returns:
            A tuple ``(bu, bi)``, which are users and items baselines.
    compute similarities(self)
        Build the similarity matrix.
        The way the similarity matrix is computed depends on the
        ``sim_options`` parameter passed at the creation of the algori
thm (see
        :ref:`similarity_measures_configuration`).
        This method is only relevant for algorithms using a similarity
measure,
        such as the :ref:`k-NN algorithms <pred_package_knn_inpired>`.
```

```
Returns:
            The similarity matrix.
    default_prediction(self)
        Used when the ``PredictionImpossible`` exception is raised dur
ing a
        call to :meth:`predict()
        <surprise.prediction_algorithms.algo_base.AlgoBase.predict>`.
Ву
        default, return the global mean of all ratings (can be overrid
den in
        child classes).
        Returns:
            (float): The mean of all ratings in the trainset.
    get_neighbors(self, iid, k)
        Return the ``k`` nearest neighbors of ``iid``, which is the in
ner id
        of a user or an item, depending on the ``user_based`` field of
        ``sim options`` (see :ref:`similarity measures configuration
`).
        As the similarities are computed on the basis of a similarity
measure,
        this method is only relevant for algorithms using a similarity
measure,
        such as the :ref:`k-NN algorithms <pred package knn inpired>`.
        For a usage example, see the :ref:`FAQ <get_k_nearest_neighbor
s>`.
        Args:
            iid(int): The (inner) id of the user (or item) for which w
e want
                the nearest neighbors. See :ref:`this note<raw_inner_n
ote>`.
            k(int): The number of neighbors to retrieve.
        Returns:
            The list of the ``k`` (inner) ids of the closest users (or
items)
            to ``iid``.
    predict(self, uid, iid, r_ui=None, clip=True, verbose=False)
        Compute the rating prediction for given user and item.
        The ``predict`` method converts raw ids to inner ids and then
calls the
        ``estimate`` method which is defined in every derived class. I
f the
        prediction is impossible (e.g. because the user and/or the ite
m is
        unknown), the prediction is set according to
        :meth:`default_prediction()
        <surprise.prediction_algorithms.algo_base.AlgoBase.default_pre</pre>
```

```
diction>`.
        Args:
            uid: (Raw) id of the user. See :ref:`this note<raw_inner_n</pre>
ote>`.
            iid: (Raw) id of the item. See :ref:`this note<raw_inner_n</pre>
ote>`.
            r_ui(float): The true rating :math:`r_{ui}`. Optional, def
ault is
                ``None``.
            clip(bool): Whether to clip the estimation into the rating
scale.
                For example, if :math:`\hat{r}_{ui}` is :math:`5.5` wh
ile the
                rating scale is :math:`[1, 5]`, then :math:`\hat{r}_{u}
i}`is
                set to :math:`5`. Same goes if :math:`\hat{r}_{ui} < 1</pre>
                Default is ``True``.
            verbose(bool): Whether to print details of the prediction.
Default
                is False.
        Returns:
            A :obj:`Prediction
                                           <surprise.prediction_algorit</pre>
hms.predictions.Prediction>` object
            containing:
            - The (raw) user id ``uid``.
            - The (raw) item id ``iid``
            - The true rating ``r_ui`` (:math:`r_{ui}`).
            - The estimated rating (:math:`\hat{r}_{ui}`).
            - Some additional details about the prediction that might
be useful
              for later analysis.
    test(self, testset, verbose=False)
        Test the algorithm on given testset, i.e. estimate all the rat
ings
        in the given testset.
        Args:
            testset: A test set, as returned by a :ref:`cross-validati
on
                itertor<use_cross_validation_iterators>` or by the
                :meth:`build_testset() <surprise.Trainset.build_testse</pre>
t>
                method.
            verbose(bool): Whether to print details for each predictio
ns.
                Default is False.
        Returns:
            A list of :class:`Prediction
                                                      <surprise.predicti</pre>
on_algorithms.predictions.Prediction>` objects
            that contains all the estimated ratings.
```

```
Data descriptors inherited from surprise.prediction_algorithms.alg
o_base.AlgoBase:
     dict
        dictionary for instance variables (if defined)
     weakref
        list of weak references to the object (if defined)
```

## best algo - fit & test

```
In [7]:
```

```
trainset, testset = train_test_split(data, test_size=0.25)
best algo.fit(trainset)
predictions = best_algo.test(testset)
print(predictions[0:2])
Computing the msd similarity matrix...
Done computing similarity matrix.
[Prediction(uid=292, iid=1291, r_ui=4.5, est=3.5127262828365318, detai
ls={'was_impossible': True, 'reason': 'Not enough neighbors.'}), Predi
ction(uid=182, iid=3326, r_ui=2.5, est=3.5127262828365318, details={'w
as_impossible': True, 'reason': 'Not enough neighbors.'})]
```

```
In [8]:
import itertools
for uid, iid, rating in itertools.islice(trainset.all_ratings(), 5):
    print(f"User {uid} rated item {iid} with a rating of {rating}")
print()
for uid, iid, rating in testset[:5]:
    print(f"User {uid} rated item {iid} with a rating of {rating}")
print()
print(trainset.n_ratings,len(testset))
User 0 rated item 0 with a rating of 5.0
User 0 rated item 213 with a rating of 3.0
User 0 rated item 801 with a rating of 4.0
User 0 rated item 1018 with a rating of 3.0
User 0 rated item 1414 with a rating of 4.0
User 292 rated item 1291 with a rating of 4.5
User 182 rated item 3326 with a rating of 2.5
User 89 rated item 56367 with a rating of 2.0
User 200 rated item 5617 with a rating of 3.5
User 232 rated item 37720 with a rating of 3.0
```

7347 2450

#### In [9]:

```
for uid, iid, rating in testset[:5]:
    print(f"User {uid} rated item {iid} with a rating of {rating}")
User 292 rated item 1291 with a rating of 4.5
```

```
User 182 rated item 3326 with a rating of 2.5
User 89 rated item 56367 with a rating of 2.0
User 200 rated item 5617 with a rating of 3.5
User 232 rated item 37720 with a rating of 3.0
```

The 'predictions' is a list of tuples of the form (user, item, actual rating, predicted rating, details). The predicted rating is est value.

## In [10]:

```
for prediction in predictions[0:5]:
    print(prediction)
```

```
item: 1291
user: 292
                                  r ui = 4.50
                                                              {'was imp
                                                 est = 3.51
ossible': True, 'reason': 'Not enough neighbors.'}
user: 182
                 item: 3326
                                  r_ui = 2.50
                                                 est = 3.51
                                                              {'was_imp
ossible': True, 'reason': 'Not enough neighbors.'}
                 item: 56367
                                                est = 3.51
user: 89
                                  r ui = 2.00
                                                              {'was_imp
ossible': True, 'reason': 'Not enough neighbors.'}
                                                est = 3.51
user: 200
                 item: 5617
                                  r_ui = 3.50
                                                              {'was_imp
ossible': True, 'reason': 'Not enough neighbors.'}
user: 232
                 item: 37720
                                  r ui = 3.00
                                                est = 3.51
                                                              {'was imp
ossible': True, 'reason': 'Not enough neighbors.'}
```

#### In [11]:

```
# Print the performance metrics
accuracy.rmse(predictions)
```

RMSE: 1.0626

## Out[11]:

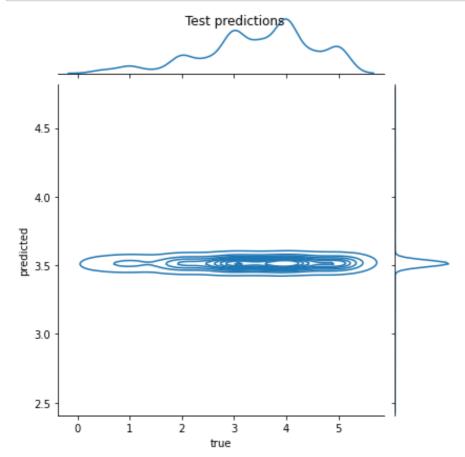
1.0626366532296367

#### In [12]:

```
true_ratings = [pred.r_ui for pred in predictions]
est ratings = [pred.est for pred in predictions]
uids = [pred.uid for pred in predictions]
```

### In [13]:

```
data=pd.DataFrame(columns=["true", "predicted"])
data["true"]=true ratings
data["predicted"]=est_ratings
g = sns.jointplot(data=data,x="true", y="predicted", kind="kde",)
g.fig.suptitle('Test predictions',fontsize=12)
plt.show()
```



## Recommend unseen books for test set users

## In [14]:

```
import pandas as pd
books=pd.read_csv('/kaggle/input/movies-and-ratings-for-recommendation-system/movie
s.csv')
#display(movies)
mapping = books.set_index("movieId")["title"].to_dict()
#print(mapping)
```

#### In [15]:

```
users=list(set(uids))
```

### In [16]:

```
# items which the user not yet evaluate
items = trainset.build_anti_testset()
for user in users[0:30]:
    user_items = list(filter(lambda x: x[0] == user, items))
    # generate recommendation
    recommendations = best_algo.test(user_items)
    if len(recommendations)>0:
        recommendations.sort(key=operator.itemgetter(3), reverse=True)
        print(f"For User {user}:")
        for r in recommendations[0:5]:
            try:
                         {mapping[r[1]]} : [{round(r[3],3)}]")
            except:
                continue
```

```
For User 1:
  American Beauty (1999) : [4.442]
  Raiders of the Lost Ark (Indiana Jones and the Raiders of the Lost A
rk) (1981) : [4.286]
  Silence of the Lambs, The (1991) : [4.276]
  Ghostbusters (a.k.a. Ghost Busters) (1984) : [4.26]
  Shawshank Redemption, The (1994): [4.247]
For User 2:
  Space Jam (1996) : [3.513]
  Mrs. Doubtfire (1993) : [3.513]
  Brazil (1985) : [3.513]
  Braveheart (1995) : [3.513]
  Ravenous (1999) : [3.513]
For User 3:
  Space Jam (1996) : [3.513]
  Mrs. Doubtfire (1993) : [3.513]
  Brazil (1985) : [3.513]
  Braveheart (1995) : [3.513]
  Ravenous (1999) : [3.513]
For User 4:
  Star Wars: Episode V - The Empire Strikes Back (1980) : [4.738]
  Alien (1979) : [4.337]
  Lord of the Rings: The Two Towers, The (2002): [4.311]
  Bourne Identity, The (2002) : [4.22]
  Lord of the Rings: The Return of the King, The (2003): [4.215]
For User 6:
  Fugitive, The (1993): [4.184]
  Batman (1989) : [3.79]
  Space Jam (1996) : [3.513]
  Mrs. Doubtfire (1993) : [3.513]
  Brazil (1985) : [3.513]
For User 7:
  Forrest Gump (1994) : [4.702]
  Lord of the Rings: The Fellowship of the Ring, The (2001): [4.56]
  Blade Runner (1982) : [4.285]
  Raiders of the Lost Ark (Indiana Jones and the Raiders of the Lost A
rk) (1981) : [4.244]
  Shawshank Redemption, The (1994): [4.23]
For User 9:
  Space Jam (1996) : [3.513]
  Mrs. Doubtfire (1993) : [3.513]
  Brazil (1985) : [3.513]
  Braveheart (1995) : [3.513]
  Ravenous (1999) : [3.513]
For User 10:
  Space Jam (1996) : [3.513]
  Mrs. Doubtfire (1993) : [3.513]
  Brazil (1985) : [3.513]
  Braveheart (1995) : [3.513]
  Ravenous (1999) : [3.513]
For User 11:
  Space Jam (1996) : [3.513]
  Mrs. Doubtfire (1993) : [3.513]
  Brazil (1985) : [3.513]
  Braveheart (1995) : [3.513]
  Ravenous (1999) : [3.513]
For User 12:
  Space Jam (1996) : [3.513]
```

```
Mrs. Doubtfire (1993) : [3.513]
  Brazil (1985) : [3.513]
  Braveheart (1995) : [3.513]
  Ravenous (1999) : [3.513]
For User 14:
  Matrix, The (1999) : [3.925]
  Space Jam (1996) : [3.513]
  Mrs. Doubtfire (1993) : [3.513]
  Brazil (1985) : [3.513]
  Braveheart (1995) : [3.513]
For User 17:
  Pulp Fiction (1994) : [4.65]
  Stargate (1994) : [4.343]
  Star Wars: Episode VI - Return of the Jedi (1983) : [4.195]
  Fifth Element, The (1997): [4.103]
  Léon: The Professional (a.k.a. The Professional) (Léon) (1994) : [4.
036]
For User 18:
  Matrix, The (1999) : [4.487]
  Spirited Away (Sen to Chihiro no kamikakushi) (2001) : [4.471]
  Pulp Fiction (1994) : [4.453]
  Saving Private Ryan (1998) : [4.38]
  Beauty and the Beast (1991) : [4.329]
For User 19:
  Usual Suspects, The (1995) : [4.733]
  Princess Bride, The (1987) : [4.706]
  Braveheart (1995) : [4.508]
  Lord of the Rings: The Fellowship of the Ring, The (2001): [4.493]
  Pulp Fiction (1994) : [4.438]
For User 20:
  Space Jam (1996) : [3.513]
  Mrs. Doubtfire (1993) : [3.513]
  Brazil (1985) : [3.513]
  Braveheart (1995) : [3.513]
  Ravenous (1999) : [3.513]
For User 21:
  Princess Bride, The (1987) : [4.743]
  Inception (2010) : [4.612]
  Silence of the Lambs, The (1991) : [4.448]
  Gladiator (2000) : [4.389]
  American Beauty (1999) : [4.38]
For User 22:
  Lord of the Rings: The Fellowship of the Ring, The (2001): [4.379]
  Star Wars: Episode V - The Empire Strikes Back (1980) : [3.691]
  Space Jam (1996) : [3.513]
  Mrs. Doubtfire (1993) : [3.513]
  Brazil (1985) : [3.513]
For User 23:
  Jurassic Park (1993) : [4.004]
  Space Jam (1996) : [3.513]
  Mrs. Doubtfire (1993) : [3.513]
  Braveheart (1995) : [3.513]
  Ravenous (1999) : [3.513]
For User 24:
  Space Jam (1996) : [3.513]
  Mrs. Doubtfire (1993) : [3.513]
  Brazil (1985) : [3.513]
  Braveheart (1995) : [3.513]
```

```
Ravenous (1999) : [3.513]
For User 25:
  Space Jam (1996) : [3.513]
  Mrs. Doubtfire (1993) : [3.513]
  Brazil (1985) : [3.513]
  Braveheart (1995) : [3.513]
  Ravenous (1999) : [3.513]
For User 26:
  Space Jam (1996) : [3.513]
  Mrs. Doubtfire (1993) : [3.513]
  Brazil (1985) : [3.513]
  Ravenous (1999) : [3.513]
  Payback (1999) : [3.513]
For User 27:
  Matrix, The (1999): [4.204]
  Terminator 2: Judgment Day (1991) : [3.833]
  Space Jam (1996) : [3.513]
  Mrs. Doubtfire (1993) : [3.513]
  Brazil (1985) : [3.513]
For User 28:
  Star Wars: Episode VI - Return of the Jedi (1983) : [4.58]
  Toy Story 2 (1999) : [4.53]
  Fight Club (1999) : [4.455]
  Silence of the Lambs, The (1991) : [4.446]
  Gladiator (2000) : [4.408]
For User 29:
  Space Jam (1996) : [3.513]
  Mrs. Doubtfire (1993) : [3.513]
  Brazil (1985) : [3.513]
  Braveheart (1995) : [3.513]
  Ravenous (1999) : [3.513]
For User 31:
  Silence of the Lambs, The (1991) : [4.657]
  Pulp Fiction (1994) : [4.42]
  Terminator 2: Judgment Day (1991) : [3.688]
  Space Jam (1996) : [3.513]
  Mrs. Doubtfire (1993) : [3.513]
For User 32:
  Space Jam (1996) : [3.513]
  Mrs. Doubtfire (1993) : [3.513]
  Brazil (1985) : [3.513]
  Braveheart (1995) : [3.513]
  Ravenous (1999) : [3.513]
For User 33:
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  Mrs. Doubtfire (1993) : [3.513]
  Brazil (1985) : [3.513]
  Braveheart (1995) : [3.513]
  Ravenous (1999) : [3.513]
For User 34:
  Silence of the Lambs, The (1991) : [4.161]
  American History X (1998) : [4.1]
  Space Jam (1996) : [3.513]
  Mrs. Doubtfire (1993) : [3.513]
  Brazil (1985) : [3.513]
For User 36:
  Space Jam (1996) : [3.513]
  Mrs. Doubtfire (1993) : [3.513]
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  Braveheart (1995) : [3.513]
  Ravenous (1999) : [3.513]
For User 37:
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  Space Jam (1996) : [3.513]
  Mrs. Doubtfire (1993) : [3.513]
  Brazil (1985) : [3.513]
  Ravenous (1999) : [3.513]
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