In [1]:

```
!pip install imblearn -q
!pip install keras -q
!pip install tensorflow -q
!pip install folium -q
!pip install seaborn -q
```

YELP Restaurants rating prediction

Get the data

Same as in EDA notbook

In [1]:

```
import pandas as pd
import folium
import numpy as np
import matplotlib
import matplotlib.pyplot as plt
from pandas.io.json import json_normalize
import re
import seaborn as sns
sns.set_style('white')
sns.set_color_codes("dark")
%matplotlib inline
%config InlineBackend.figure_format = 'retina'
```

In [2]:

```
df = pd.read_csv("../data/data_clean_new.csv",
                          encoding='utf_8',
                          dtype = 'unicode',
                          parse_dates = True,
                          infer_datetime_format = True,
                          low_memory=False)
df = df.drop("Unnamed: 0", axis = 1)
```

Preprocess data

In [4]:

```
df.head(3)
```

Out[4]:

	address	business_id	city	is_open	latitude	longitude
0	30 Eglinton Avenue W	QXAEGFB4oINsVuTFxEYKFQ	Mississauga	1	43.6054989743	-79.652288909
1	10110 Johnston Rd, Ste 15	gnKjwL_1w79qoiV3IC_xQQ	Charlotte	1	35.092564	-80.859132
2	2450 E Indian School Rd	1Dfx3zM-rW4n-31KeC8sJg	Phoenix	1	33.4951941	-112.0285876

3 rows × 78 columns

In [5]:

```
df.stars.value_counts()
```

Out[5]:

```
3.5    12833
4.0    12816
3.0     9421
4.5     5881
2.5     5080
2.0     2771
1.5      936
5.0      931
1.0      217
Name: stars, dtype: int64
```

In [3]:

```
#convert columns to the boolean datatype when we find the vlaue "True" or "False" in th
e column
for column in df.columns :
    if df[column][0] == 'True' or df[column][0] =='False':
        df[column] = df[column]=='True'
    #Often we find a True or False in the first line
    #This tests if the column is a boolean by using the first row for efficiency

    #otherwise we test if we find a True or False value in the whole column
    elif "True" in df[column].values :
        df[column] = df[column]=='True'
    elif "False" in df[column].values :
        df[column] = df[column]=='True'
```

In [4]:

```
cuisine_type = ["American (New)","American (Traditional)","Arts & Entertainment","Asian
Fusion","Bakeries","Barbeque","Bars",
"Beer","Breakfast & Brunch","Buffets","Burgers","Cafes","Canadian (New)","Caribbean","C
aterers","Chicken Wings",
"Chinese","Cocktail Bars","Coffee & Tea","Comfort Food","Delis","Desserts","Diners","Et
hnic Food",
"Event Planning & Services","Fast Food","Food","Food Delivery Services","French","Gastr
opubs","Gluten-Free",
"Greek","Grocery","Halal","Hot Dogs","Ice Cream & Frozen Yogurt","Indian","Italian","Ja
panese","Juice Bars & Smoothies",
"Korean","Latin American","Lounges","Mediterranean","Mexican","Middle Eastern","Nightli
fe","Pizza","Pubs",
"Salad","Sandwiches","Seafood","Soup","Specialty Food","Sports Bars","Steakhouses","Sus
hi Bars","Tex-Mex",
"Thai","Vegan","Vegetarian","Vietnamese","Wine & Spirits","Wine Bars"]
```

In [5]:

```
#The cuisine types have 1 or 0 instead of True/False
for column in df[cuisine_type] :
    df[column] = df[column]=="1"
```

In [9]:

```
df.columns
```

Out[9]:

```
Index(['address', 'business_id', 'city', 'is_open', 'latitude', 'longitud
e',
       'name', 'postal_code', 'review_count', 'stars', 'state', 'Price',
       'American (New)', 'American (Traditional)', 'Arts & Entertainment',
       'Asian Fusion', 'Bakeries', 'Barbeque', 'Bars', 'Beer',
       'Breakfast & Brunch', 'Buffets', 'Burgers', 'Cafes', 'Canadian (Ne
w)',
       'Caribbean', 'Caterers', 'Chicken Wings', 'Chinese', 'Cocktail Bar
s',
       'Coffee & Tea', 'Comfort Food', 'Delis', 'Desserts', 'Diners',
       'Ethnic Food', 'Event Planning & Services', 'Fast Food', 'Food',
       'Food Delivery Services', 'French', 'Gastropubs', 'Gluten-Free',
       'Greek', 'Grocery', 'Halal', 'Hot Dogs', 'Ice Cream & Frozen Yogur
t',
       'Indian', 'Italian', 'Japanese', 'Juice Bars & Smoothies', 'Korea
n',
       'Latin American', 'Lounges', 'Mediterranean', 'Mexican',
       'Middle Eastern', 'Nightlife', 'Pizza', 'Pubs', 'Salad', 'Sandwiche
s',
       'Seafood', 'Soup', 'Specialty Food', 'Sports Bars', 'Steakhouses',
       'Sushi Bars', 'Tex-Mex', 'Thai', 'Vegan', 'Vegetarian', 'Vietnames
e',
       'Wine & Spirits', 'Wine Bars', 'Anymusic', 'name_length'],
      dtype='object')
```

In [6]:

```
df['stars']=df['stars'].astype('float')
df.Price = pd.to_numeric(df.Price, errors='coerce')
df = df[np.isfinite(df['Price'])]
#df["Price"]= df["Price"].astype(int)

df["review_count"]= df["review_count"].astype(int)
df["name_length"]= df["name_length"].astype(int)
df["name"]= df["name"].astype(str)
df["address"]= df["address"].astype(str)

df['latitude'] = df['latitude'].astype(float)
df['longitude'] = df['longitude'].astype(float)
```

In [11]:

```
df.dtypes
```

Out[11]:

```
address                      object
business_id                  object
city                         object
is_open                      object
latitude                    float64
longitude                   float64
name                         object
postal_code                  object
review_count                  int32
stars                       float64
state                        object
Price                       float64
American (New)                 bool
American (Traditional)         bool
Arts & Entertainment           bool
Asian Fusion                   bool
Bakeries                       bool
Barbeque                       bool
Bars                           bool
Beer                           bool
Breakfast & Brunch             bool
Buffets                        bool
Burgers                        bool
Cafes                          bool
Canadian (New)                 bool
Caribbean                      bool
Caterers                       bool
Chicken Wings                  bool
Chinese                        bool
Cocktail Bars                  bool
                            ...
Indian                         bool
Italian                        bool
Japanese                       bool
Juice Bars & Smoothies         bool
Korean                         bool
Latin American                 bool
Lounges                        bool
Mediterranean                  bool
Mexican                        bool
Middle Eastern                 bool
Nightlife                      bool
Pizza                          bool
Pubs                           bool
Salad                          bool
Sandwiches                     bool
Seafood                        bool
Soup                           bool
Specialty Food                 bool
Sports Bars                    bool
Steakhouses                    bool
Sushi Bars                     bool
Tex-Mex                        bool
Thai                           bool
Vegan                          bool
Vegetarian                     bool
Vietnamese                     bool
Wine & Spirits                 bool
Wine Bars                      bool
```

```
Anymusic                     bool
name_length                 int32
Length: 78, dtype: object
```

EDA

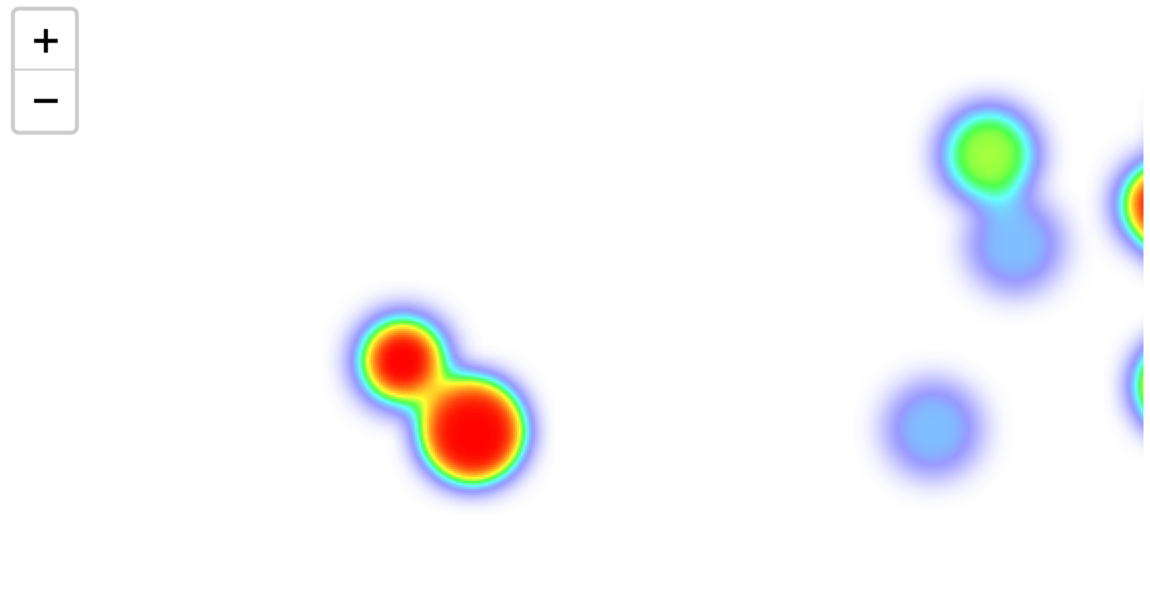
Heat map

Let's start by visualizing where the restaurants in our dataset are located

In [100]:

```python
from folium import plugins
from folium.plugins import HeatMap


# Make an empty map
m = folium.Map(location=[28,-90], tiles="OpenStreetMap", zoom_start=4)

# Filter the DF for rows, then columns, then remove NaNs
heat_df = df[['latitude', 'longitude']]
heat_df = heat_df.dropna(axis=0, subset=['latitude','longitude'])

# List comprehension to make out list of lists
heat_data = [[row['latitude'],row['longitude']] for index, row in heat_df.iterrows()]

# Plot it on the map
HeatMap(heat_data).add_to(m)

# show the map
m
```

Out[100]:



Leaflet (https://leafletjs.com) | Data by © OpenStreetMap (http://openstreetmap.org), under ODbL (http://www.openstreetmap.org/copyright).

We can see that our data is only restaurants from North America.

Stars on yelp

This will be the value that we want to predict, let's take a look.

In [13]:

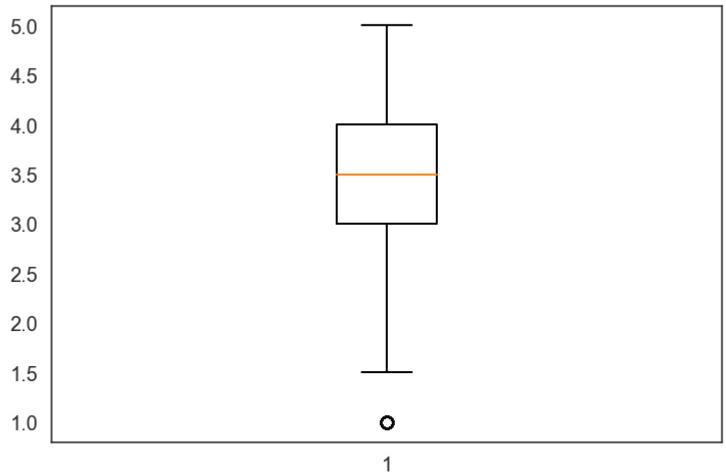
```
df.stars.describe()
```

Out[13]:

```
count    50839.000000
mean         3.447717
std          0.765024
min          1.000000
25%          3.000000
50%          3.500000
75%          4.000000
max          5.000000
Name: stars, dtype: float64
```

In [14]:

```
box_plot_data = df['stars'].astype("float")
plt.boxplot(box_plot_data)
plt.show()
```



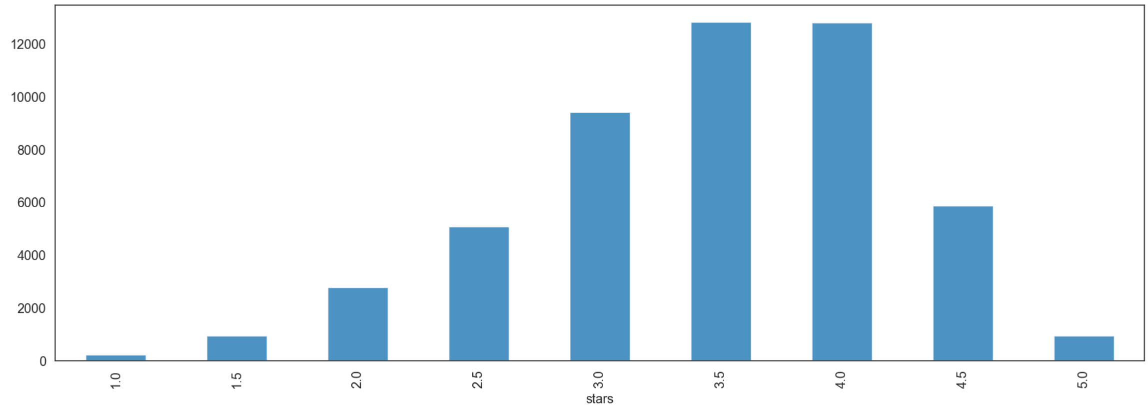
The median is 3.5 stars rating. We can see that we have an outlier, the 1 star ratings.

In [15]:

```
r1 = df[["business_id","stars"]].groupby(["stars"]).count()
r1.plot.bar(x=None,
            y=None,
            figsize=(15,5),
            alpha = 0.8, # make the plot 20% transparent
            legend = None,
           )
```

Out[15]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2b4c94987f0>
```



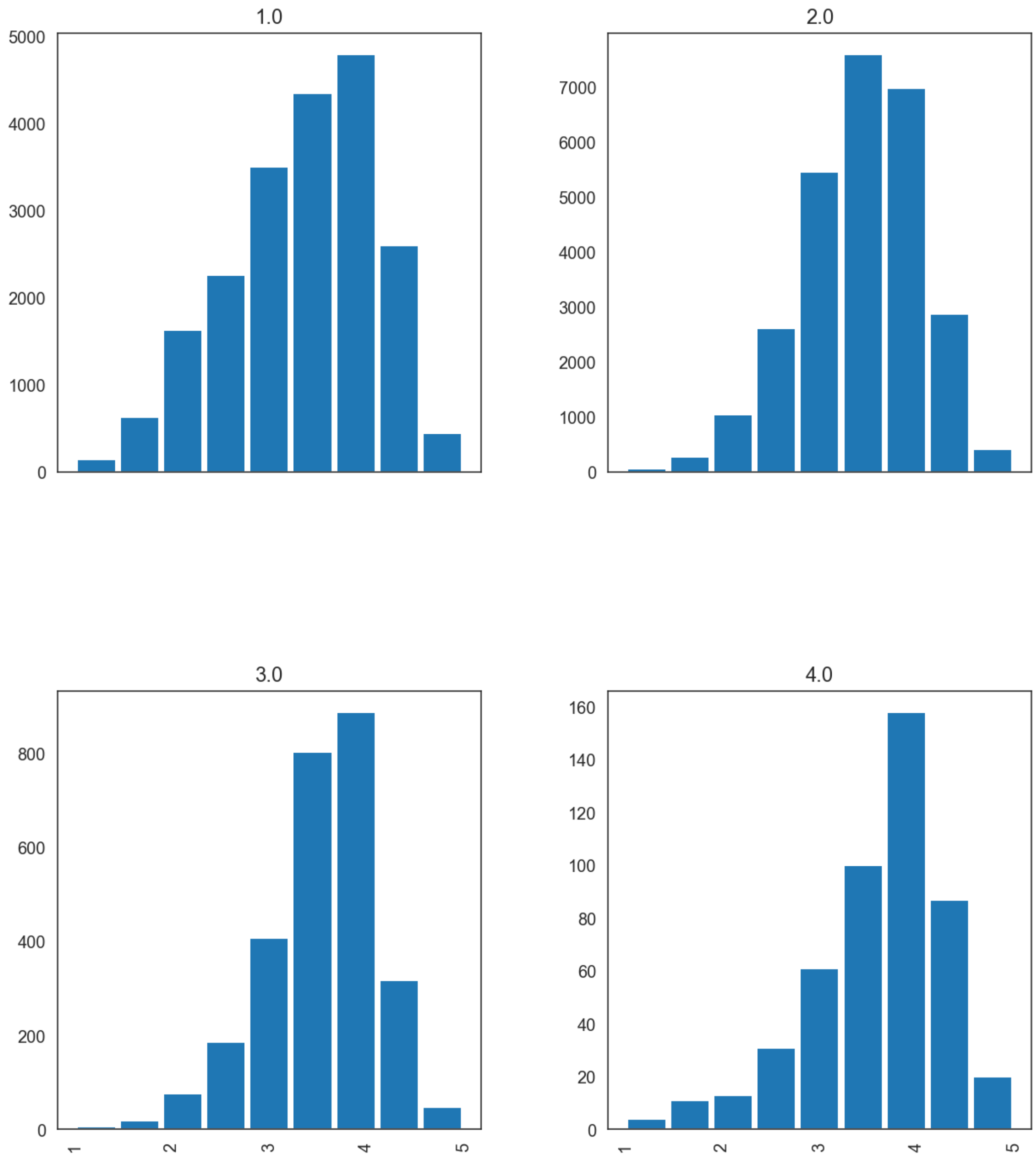
This barplot shows that we have a little bit left-skewed distribution with most common ratings of 3.5 and 4.

Price

We think that this will be an important feature so let's get som insights

In [16]:

```
ax = df.hist(column="stars", by='Price',bins=9, grid=False, figsize=(10,12), layout=(2,
2), sharex=True, zorder=2, rwidth=0.9)
```



1.0
2.0
3.0
4.0

On this graph we ploted the restaurants price classes (from 1 to 4) by stars. We can see the different distributions of ratings depending on the price category.

It can be spotted that the higher the price, the less is the number of bad-rated restaurants. It means that restaurants are trying to be worth its price.

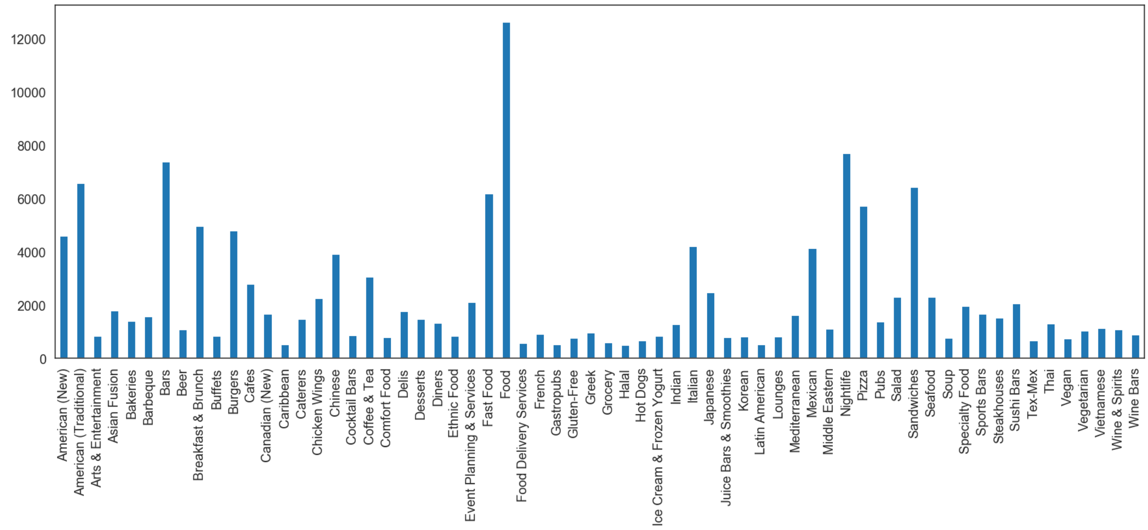
Cuisine types

In [17]:

```
r2 = df[cuisine_type].sum()
r2.plot.bar(x=None, y=None, figsize = (15, 5))
```

Out[17]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2b4c97be6d8>
```



Since we have a lot of cuisine type we will analyze the top 20 We also remove the first 3 cuisine types (Food, Bars and Nightlife) since we don't

In [7]:

```
top20_cuisines = list(df[cuisine_type].sum().sort_values(ascending=False).index[3:23])
top20_cuisines
```

Out[7]:

```
['American (Traditional)',
 'Sandwiches',
 'Fast Food',
 'Pizza',
 'Breakfast & Brunch',
 'Burgers',
 'American (New)',
 'Italian',
 'Mexican',
 'Chinese',
 'Coffee & Tea',
 'Cafes',
 'Japanese',
 'Seafood',
 'Salad',
 'Chicken Wings',
 'Event Planning & Services',
 'Sushi Bars',
 'Specialty Food',
 'Asian Fusion']
```

In [8]:

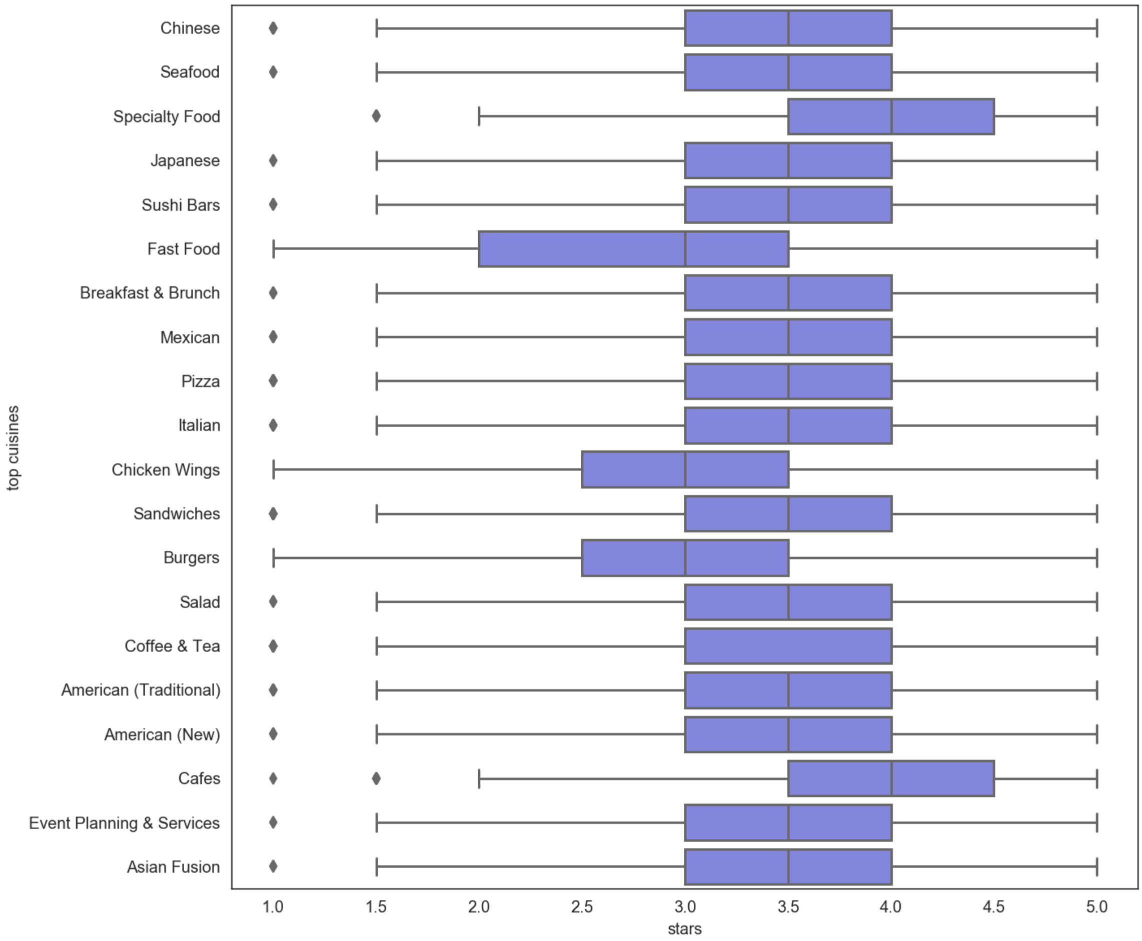
```
df2 = df.copy() #create new DataFrame
st = df2.loc[:, top20_cuisines].stack()

all_ids = pd.Series(st.index.get_level_values(1),
                    st.index.get_level_values(0),
                    name='top cuisines')[st.values]

df2 = df2.join(all_ids, how='left').dropna()
```

In [9]:

```
plt.figure(figsize = (10, 10))
sns.boxplot(data = df2[["top cuisines", "stars"]], x= "stars", y="top cuisines", color=
matplotlib.colors.to_hex('#7479e8'))
```

Out[9]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x21e55559688>
```



We can see that Fast Food, Chicken Wings and Burgers have a lower star ratings median. At the same time, Cafes and Specialty Food places have median rating above average median.

In [10]:

```
df2.stars = df2.stars.astype(float)
avg_ratings_cuisine = pd.DataFrame(df2.groupby("top cuisines")["stars"].mean())
avg_ratings_cuisine
```

Out[10]:

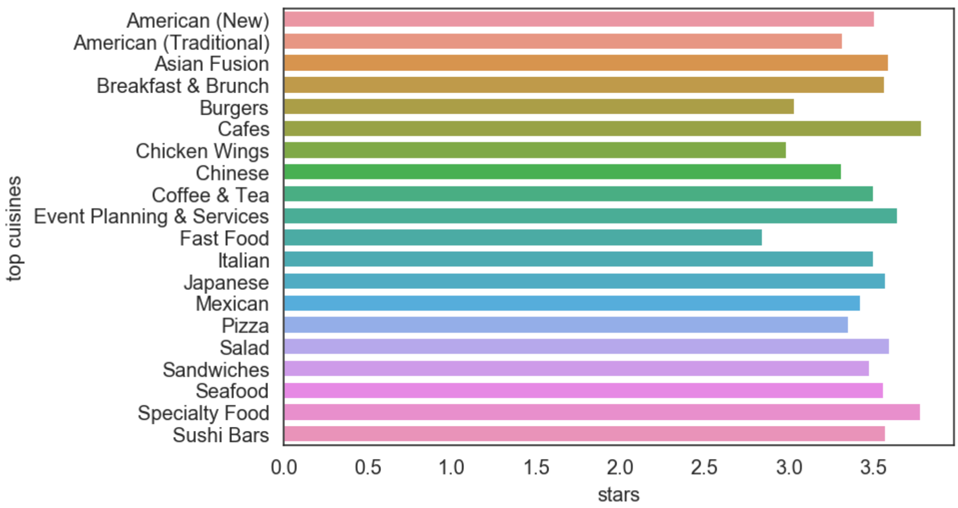
top cuisines	stars
American (New)	3.510193
American (Traditional)	3.321602
Asian Fusion	3.593610
Breakfast & Brunch	3.572063
Burgers	3.038101
Cafes	3.790196
Chicken Wings	2.987556
Chinese	3.318252
Coffee & Tea	3.506048
Event Planning & Services	3.649859
Fast Food	2.846645
Italian	3.507121
Japanese	3.576039
Mexican	3.429625
Pizza	3.356643
Salad	3.600738
Sandwiches	3.484052
Seafood	3.565415
Specialty Food	3.785568
Sushi Bars	3.579203

In [11]:

```
sns.barplot(data= avg_ratings_cuisine, x = "stars", y= avg_ratings_cuisine.index )
```

Out[11]:

```
&lt;matplotlib.axes._subplots.AxesSubplot at 0x21e5501b0c8&gt;
```



Base rate

The base rate is the size of the most common class divided by the size of the dataset. Our accuracy should be better than the default rate

In [23]:

```
df.stars.dtypes
```

Out[23]:

```
dtype('float64')
```

In [24]:

```
print("The most common class for the ratings is", df["stars"].mode()[0])

baseRate = df[df["stars"] == 3.5].count()["stars"] / df["stars"].count()
print("The baserate is :", baseRate)
```

```
The most common class for the ratings is 3.5
The baserate is : 0.25228663034284704
```

Preprocess data for models

The outlier we identified earlier, the 1 star rating, does not contain enough restaurants (only 216), thus we decided to drop it. We also drop string columns, which will not help in prediction (They are mainly related to geography).

In [25]:

```
from sklearn import preprocessing
from sklearn import utils
```

In [26]:

```
df.columns
```

Out[26]:

```
Index(['address', 'business_id', 'city', 'is_open', 'latitude', 'longitud
e',
       'name', 'postal_code', 'review_count', 'stars', 'state', 'Price',
       'American (New)', 'American (Traditional)', 'Arts & Entertainment',
       'Asian Fusion', 'Bakeries', 'Barbeque', 'Bars', 'Beer',
       'Breakfast & Brunch', 'Buffets', 'Burgers', 'Cafes', 'Canadian (Ne
w)',
       'Caribbean', 'Caterers', 'Chicken Wings', 'Chinese', 'Cocktail Bar
s',
       'Coffee & Tea', 'Comfort Food', 'Delis', 'Desserts', 'Diners',
       'Ethnic Food', 'Event Planning & Services', 'Fast Food', 'Food',
       'Food Delivery Services', 'French', 'Gastropubs', 'Gluten-Free',
       'Greek', 'Grocery', 'Halal', 'Hot Dogs', 'Ice Cream & Frozen Yogur
t',
       'Indian', 'Italian', 'Japanese', 'Juice Bars & Smoothies', 'Korea
n',
       'Latin American', 'Lounges', 'Mediterranean', 'Mexican',
       'Middle Eastern', 'Nightlife', 'Pizza', 'Pubs', 'Salad', 'Sandwiche
s',
       'Seafood', 'Soup', 'Specialty Food', 'Sports Bars', 'Steakhouses',
       'Sushi Bars', 'Tex-Mex', 'Thai', 'Vegan', 'Vegetarian', 'Vietnames
e',
       'Wine & Spirits', 'Wine Bars', 'Anymusic', 'name_length'],
      dtype='object')
```

In [27]:

```
X = df[df['stars'] != 1.0]
X = X.drop(['stars', "name", "address", "business_id", "city", "state", 'postal_code',
'latitude', 'longitude'], axis = 1)
y = df[df["stars"] != 1.0]["stars"]
```

In [28]:

```
y.value_counts()
```

Out[28]:

```
3.5    12826
4.0    12809
3.0     9414
4.5     5875
2.5     5075
2.0     2762
1.5      933
5.0      929
Name: stars, dtype: int64
```

In [29]:

```
#SMOTE does not handle categorical data, we could also use SMOTE-NC
```

In [30]:

```
X.Anymusic = X.Anymusic.astype(bool)
X.is_open = X.is_open.astype(bool)
```

In [31]:

```
lab_enc = preprocessing.LabelEncoder()
encoded_y = lab_enc.fit_transform(y) #we label encode the star ratings
#X.Price = lab_enc.fit_transform(X.Price)
```

We divide our data into train and test.

In [32]:

```
from sklearn.model_selection import train_test_split, GridSearchCV
from pprint import pprint
from time import time
```

In [33]:

```
# split train/test
X_train, X_test, y_train, y_test = train_test_split(X, encoded_y, test_size=0.2, random
_state=72)
```

Now, we decided to try two methods to fight severe class imbalance. Just downsampling is not an option (then each class will have 900 observations), thus, first we tried upsampling our train data and the we wanted to try to combine the two methods by upsampling all the classes below the mean and downsampling the classes above it.

For upsampling we used a technique called SMOTE (**S**ynthetic **M**inority **O**ver-sampling **TE**chnique) that will synthesize new minority instances. So in our case we will basically generate "fake" restaurants based on other on the data set we have, for more details check out : [http://rikunert.com/SMOTE_explained (http://rikunert.com/SMOTE_explained)](http://rikunert.com/SMOTE_explained) .

For downsampling we used the NearMiss methode

"first, the method calculates the distances between all instances of the majority class and the instances of the minority class. Then k instances of the majority class that have the smallest distances to those in the minority class are selected. If there are n instances in the minority class, the "nearest" method will result in k*n instances of the majority class."

source : [https://towardsdatascience.com/sampling-techniques-for-extremely-imbalanced-data-part-i-under-sampling-a8dbc3d8d6d8 (https://towardsdatascience.com/sampling-techniques-for-extremely-imbalanced-data-part-i-under-sampling-a8dbc3d8d6d8)](https://towardsdatascience.com/sampling-techniques-for-extremely-imbalanced-data-part-i-under-sampling-a8dbc3d8d6d8)

In [34]:

```
from imblearn.over_sampling import SMOTE
from imblearn.under_sampling import NearMiss
```

```
Using TensorFlow backend.
```

In [35]:

```
unique, counts = np.unique(encoded_y, return_counts=True)
dict(zip(unique, counts))
```

Out[35]:

```
{0: 933, 1: 2762, 2: 5075, 3: 9414, 4: 12826, 5: 12809, 6: 5875, 7: 929}
```

In [36]:

```
#upsamples all the train data
X_resampled, y_resampled = SMOTE(random_state = 72).fit_resample(X_train, y_train)
```

In [37]:

```
med_cl_cnt= int(pd.Series(y_train).value_counts().median()) # median of obs over classe
s
med_cl_cnt
```

Out[37]:

```
4379
```

In [38]:

```
unique, counts = np.unique(y_train, return_counts=True)
dict(zip(unique, counts))
```

Out[38]:

```
{0: 736, 1: 2202, 2: 4056, 3: 7539, 4: 10268, 5: 10266, 6: 4702, 7: 729}
```

In [39]:

```
#downsamples and upsamples the train data (based on median)
X_resampled2, y_resampled2 = NearMiss(sampling_strategy = {3:med_cl_cnt, 4:med_cl_cnt,
5:med_cl_cnt, 6:med_cl_cnt}).fit_resample(X_train, y_train) #downsampling
X_resampled2, y_resampled2 = SMOTE(random_state = 72, sampling_strategy = {7:med_cl_cnt
, 0:med_cl_cnt, 1:med_cl_cnt, 2:med_cl_cnt}).fit_resample(X_resampled2, y_resampled2) #
upsampling
```

In [40]:

```
unique, counts = np.unique(y_resampled2, return_counts=True)
dict(zip(unique, counts))
```

Out[40]:

```
{0: 4379, 1: 4379, 2: 4379, 3: 4379, 4: 4379, 5: 4379, 6: 4379, 7: 4379}
```

Specify parameters values for grid search:

In [41]:

```
parametersRF = {
    'n_estimators': (100,200,300),
    'max_depth': (10,20,30)
}
parametersLR = {
    'C': (0.1, 1,100),
    'solver': (['saga','lbfgs'])
}
parametersNN = {
    'epochs': ([10, 100]),
    'batch_size': ([20,30])
}
```

Logistic Regression

In [42]:

```
from sklearn.linear_model import LogisticRegressionCV, LogisticRegression
```

We tried three different samples of data: normal, upsampled, upsampled+downsampled

We found that for logistic regression the best result is produced with the normal data

In [44]:

```
# decomment, if need to run best model with other params
LR = LogisticRegression(solver='lbfgs',C=0.1, max_iter=2000, multi_class = "auto")
LR.fit(X_train, y_train)
```

```
C:\Users\David\Anaconda3\lib\site-packages\sklearn\linear_model\_logistic.
py:939: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown i
n:
    https://scikit-learn.org/stable/modules/preprocessing.html.
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-reg
ression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
```

Out[44]:

```
LogisticRegression(C=0.1, class_weight=None, dual=False, fit_intercept=Tru
e,
                   intercept_scaling=1, l1_ratio=None, max_iter=2000,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=None, solver='lbfgs', tol=0.0001, verbose=
0,
                   warm_start=False)
```

In [45]:

```
if __name__ == "__main__":
    # multiprocessing requires the fork to happen in a __main__ protected
    # block

    # find the best parameters for both the feature extraction and the
    # classifier
    grid_search = GridSearchCV(LR, parametersLR, cv=2,
                               n_jobs=-1, verbose=1,scoring='accuracy')

    print("Performing grid search...")
    #print("pipeline:", [name for name, _ in pipeline2.steps])
    print("parameters:")
    pprint(parametersLR)
    t0 = time()
    grid_search.fit(X_train, y_train)
    print("done in %0.3fs" % (time() - t0))
    print()

    print("Best score for Logistic Regression: %0.3f" % grid_search.best_score_)
    print("Best parameters set:")
    best_parameters = grid_search.best_estimator_.get_params()
    for param_name in sorted(parametersLR.keys()):
        print("\t%s: %r" % (param_name, best_parameters[param_name]))
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent worker
s.

Performing grid search...
parameters:
{'C': (0.1, 1, 100), 'solver': ['saga', 'lbfgs']}
Fitting 2 folds for each of 6 candidates, totalling 12 fits

[Parallel(n_jobs=-1)]: Done  10 out of  12 | elapsed:  1.1min remaining:
13.6s
[Parallel(n_jobs=-1)]: Done  12 out of  12 | elapsed:  1.1min finished


done in 112.545s

Best score for Logistic Regression: 0.303
Best parameters set:
        C: 0.1
        solver: 'lbfgs'

C:\Users\David\Anaconda3\lib\site-packages\sklearn\linear_model\_logistic.
py:939: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown i
n:
    https://scikit-learn.org/stable/modules/preprocessing.html.
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-reg
ression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
```

The best model according to gridsearch is the one we tested at the beginning with lbfgs solver and C equal to 0.1

In [46]:

```
# train accuracy
LR.score(X_train, y_train)
```

Out[46]:

```
0.3085337547533212
```

In [47]:

```
# test accuracy
LR.score(X_test, y_test)
```

Out[47]:

```
0.2973827160493827
```

In [48]:

```
from sklearn.metrics import classification_report
target_names = ["1.5","2","2.5","3","3.5","4","4.5","5"]

print(classification_report(y_test, LR.predict(X_test), target_names= target_names))
```

```
              precision    recall  f1-score   support

         1.5       0.00      0.00      0.00       197
           2       0.27      0.22      0.24       560
         2.5       0.22      0.05      0.09      1019
           3       0.26      0.15      0.19      1875
         3.5       0.29      0.45      0.35      2558
           4       0.32      0.53      0.40      2543
         4.5       0.44      0.06      0.11      1173
           5       0.00      0.00      0.00       200

    accuracy                           0.30     10125
   macro avg       0.22      0.18      0.17     10125
weighted avg       0.29      0.30      0.26     10125


C:\Users\David\Anaconda3\lib\site-packages\sklearn\metrics\_classificatio
n.py:1268: UndefinedMetricWarning: Precision and F-score are ill-defined a
nd being set to 0.0 in labels with no predicted samples. Use `zero_divisio
n` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

Our test accuracy is above the baserate but it isn't really a good result since we cannot predict 1.5 and 5 stars.

Random Forest Classifier

Here we will try both data samples, but still we believe that sticking to one method of upsampling is better (at least more common).

In [49]:

```
from sklearn.ensemble import RandomForestClassifier, ExtraTreesClassifier
from sklearn.model_selection import cross_val_score
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import make_scorer
MAE = make_scorer(mean_absolute_error)
folds = 3
```

In [50]:

```
clf = RandomForestClassifier(n_estimators = 200,max_depth = 30)
clf.fit(X_resampled, y_resampled)
```

Out[50]:

```
RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=None,
                       criterion='gini', max_depth=30, max_features='aut
o',
                       max_leaf_nodes=None, max_samples=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=200,
                       n_jobs=None, oob_score=False, random_state=None,
                       verbose=0, warm_start=False)
```

In [51]:

```
if __name__ == "__main__": # just for multiprocessing purposes
    grid_search = GridSearchCV(clf, parametersRF, cv=3,
                               n_jobs=-1, verbose=1,scoring='accuracy')

    print("Performing grid search...")
    #print("Random Forest:", [name for name, _ in clf.steps])
    print("parameters:")
    pprint(parametersRF)
    t0 = time()
    grid_search.fit(X_resampled2, y_resampled2)
    print("done in %0.3fs" % (time() - t0))
    print()

    print("Best score for Random Forest: %0.3f" % grid_search.best_score_)
    print("Best parameters set:")
    best_parameters = grid_search.best_estimator_.get_params()
    for param_name in sorted(parametersRF.keys()):
        print("\t%s: %r" % (param_name, best_parameters[param_name]))
```

```
Performing grid search...
parameters:
{'max_depth': (10, 20, 30), 'n_estimators': (100, 200, 300)}
Fitting 3 folds for each of 9 candidates, totalling 27 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent worker
s.
[Parallel(n_jobs=-1)]: Done  27 out of  27 | elapsed:   40.2s finished

done in 49.294s

Best score for Random Forest: 0.401
Best parameters set:
        max_depth: 30
        n_estimators: 200
```

In [52]:

```
clf = RandomForestClassifier(n_estimators = 300,max_depth = 30)
clf.fit(X_resampled, y_resampled)
```

Out[52]:

```
RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=None,
                       criterion='gini', max_depth=30, max_features='aut
o',
                       max_leaf_nodes=None, max_samples=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=300,
                       n_jobs=None, oob_score=False, random_state=None,
                       verbose=0, warm_start=False)
```

In [53]:

```
clf2 = RandomForestClassifier(n_estimators = 300,max_depth = 30)
clf2.fit(X_resampled2, y_resampled2)
```

Out[53]:

```
RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=None,
                       criterion='gini', max_depth=30, max_features='aut
o',
                       max_leaf_nodes=None, max_samples=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=300,
                       n_jobs=None, oob_score=False, random_state=None,
                       verbose=0, warm_start=False)
```

In [54]:

```
print("Train accuracy :", clf.score(X_resampled, y_resampled))
print("Test accuracy :", clf.score(X_test, y_test))
```

```
Train accuracy : 0.8866867939228672
Test accuracy : 0.2854320987654321
```

In [55]:

```
print("Train acc upsample + downsample :", clf2.score(X_resampled2, y_resampled2))
print("Test acc upsample + downsample :", clf2.score(X_test, y_test))
```

```
Train acc upsample + downsample : 0.853505366522037
Test acc upsample + downsample : 0.21175308641975307
```

Report for upsampling:

In [56]:

```
print(classification_report(y_test, clf.predict(X_test), target_names= target_names))
```

```
              precision    recall  f1-score   support

         1.5       0.21      0.33      0.26       197
           2       0.20      0.22      0.21       560
         2.5       0.20      0.17      0.19      1019
           3       0.26      0.22      0.24      1875
         3.5       0.32      0.36      0.34      2558
           4       0.35      0.36      0.35      2543
         4.5       0.27      0.22      0.24      1173
           5       0.09      0.14      0.11       200

    accuracy                           0.29     10125
   macro avg       0.24      0.25      0.24     10125
weighted avg       0.29      0.29      0.28     10125
```

Report for upsampling + downsampling:

In [57]:

```
print(classification_report(y_test, clf2.predict(X_test), target_names= target_names))
```

```
              precision    recall  f1-score   support

         1.5       0.18      0.29      0.22       197
           2       0.19      0.19      0.19       560
         2.5       0.15      0.23      0.18      1019
           3       0.26      0.17      0.21      1875
         3.5       0.27      0.17      0.21      2558
           4       0.27      0.15      0.19      2543
         4.5       0.18      0.50      0.27      1173
           5       0.10      0.14      0.12       200

    accuracy                           0.21     10125
   macro avg       0.20      0.23      0.20     10125
weighted avg       0.24      0.21      0.21     10125
```

For random forest upsampling data produces the best result

At the end, we would like to use mean absolute error as a performance metric for our models, because predicting rating of the restaurant is a classification with ordinal variable. Thus, misclassification of 0.5 star is better than 1.5 stars.

In [58]:

```
MAE_RF = cross_val_score(clf,
    X_resampled,
    y_resampled,
    cv=folds,
    scoring=MAE)
```

In [60]:

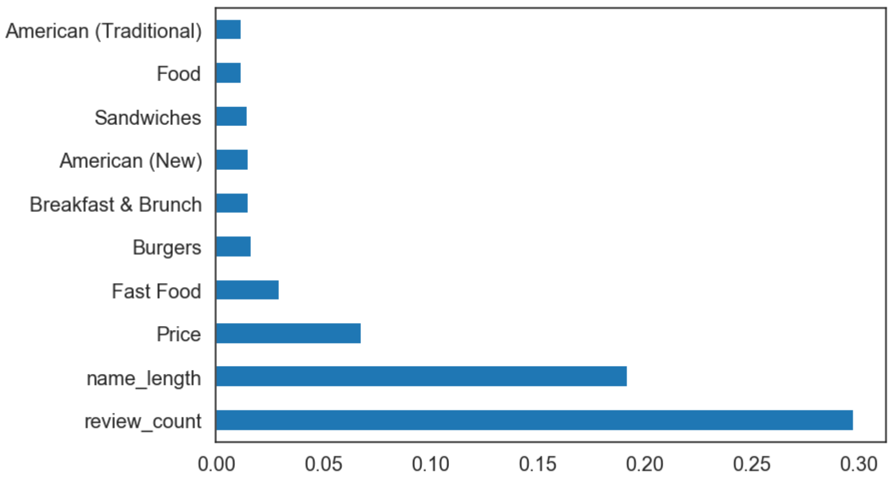
```
print("Random forest MAE :", np.mean(MAE_RF))
```

```
Random forest MAE : 0.7039451011343688
```

In [61]:

```
model = ExtraTreesClassifier(n_estimators=100)
model.fit(X_resampled, y_resampled)
print(model.feature_importances_) #use inbuilt class feature_importances of tree based
 classifiers
#plot graph of feature importances for better visualization
feat_importances = pd.Series(model.feature_importances_, index=X.columns)
feat_importances.nlargest(10).plot(kind='barh')
plt.show()
```

```
[0.         0.29800039 0.06820441 0.01515998 0.01201516 0.00526027
 0.00802179 0.00507183 0.00744214 0.00556076 0.00220836 0.01545872
 0.00509805 0.01657808 0.00858648 0.00836663 0.0033357  0.00407641
 0.00960738 0.00715187 0.00270939 0.00863415 0.00569523 0.0076955
 0.00604288 0.00678697 0.00228925 0.00656537 0.02955366 0.01219629
 0.0034931  0.00437711 0.00295202 0.0050741  0.00540909 0.00348327
 0.00382619 0.00517109 0.00440155 0.00645447 0.01103626 0.00710901
 0.00407904 0.00457244 0.0036369  0.00334613 0.00613572 0.01005864
 0.00573326 0.00647433 0.0103302  0.00414828 0.00968939 0.01475103
 0.00954069 0.00445216 0.00615938 0.00347768 0.00608864 0.00646778
 0.00301797 0.00558962 0.00402245 0.00481717 0.00558759 0.00218616
 0.00257155 0.0045649  0.19234052]
```



Neural network

Here we are implementing neural network with basic architecture on not sampled data.

In [62]:

```
from keras.models import Sequential
from keras.layers.core import Dense, Dropout, Activation
from keras import optimizers
from keras.utils import np_utils
from keras.wrappers.scikit_learn import KerasClassifier
np.random.seed(1143)
```

In [63]:

```
def model_NN():
    model = Sequential()
    model.add(Dense(512, input_shape=(69,)))
    model.add(Activation('relu')) # An "activation" is just a non-linear function appli
ed to the output
                                  # of the layer above. Here, with a "rectified linear uni
t"
                                  # we clamp all values below 0 to 0.

    model.add(Dropout(0.2))   # Dropout helps protect the model from memorizing or "ove
rfitting" the training data
    model.add(Dense(8))
    model.add(Activation('softmax')) # This special "softmax" activation among other th
ings,
                                     # ensures the output is a valid probaility distributio
n, that is
                                     # that its values are all non-negative and sum to 1.
    #optimizer = optimizers.Adam(lr=0.01, decay=1e-6)
    optimizer = optimizers.SGD(lr=0.01, decay=1e-6, momentum=0.9, nesterov=True)
    model.compile(loss='categorical_crossentropy', optimizer=optimizer, metrics=['accur
acy'])
    return model
```

In [64]:

```
model = KerasClassifier(build_fn= model_NN, epochs=100, batch_size=10, verbose=0)
```

In [65]:

```
X = df[df["stars"] != 1]
X = X.drop(['stars', "name", "address", "business_id", "city", "state", 'postal_code',
"longitude", "latitude"], axis = 1)
y = df[df["stars"] !=1]["stars"]
```

In [66]:

```
#nb_classes = len(y.value_counts())

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=7
2)
```

In [67]:

```
from keras.utils import to_categorical

y_train = to_categorical(y_train, num_classes=8)
y_test = to_categorical(y_test, num_classes=8)
```

In [68]:

```
model_hist = model.fit(X_train, y_train,
                       batch_size=64, epochs=10,
                       verbose=1, validation_split=0.2)
```

```
Train on 32398 samples, validate on 8100 samples
Epoch 1/10
32398/32398 [==============================] - 1s 36us/step - loss: 1.6791
- accuracy: 0.4296 - val_loss: 1.1909 - val_accuracy: 0.4381
Epoch 2/10
32398/32398 [==============================] - 1s 34us/step - loss: 1.1915
- accuracy: 0.4320 - val_loss: 1.1761 - val_accuracy: 0.3926
Epoch 3/10
32398/32398 [==============================] - 1s 35us/step - loss: 1.1698
- accuracy: 0.4339 - val_loss: 1.1749 - val_accuracy: 0.4391
Epoch 4/10
32398/32398 [==============================] - 1s 37us/step - loss: 1.1637
- accuracy: 0.4388 - val_loss: 1.1567 - val_accuracy: 0.4401
Epoch 5/10
32398/32398 [==============================] - 1s 33us/step - loss: 1.1609
- accuracy: 0.4353 - val_loss: 1.1558 - val_accuracy: 0.4399
Epoch 6/10
32398/32398 [==============================] - 1s 34us/step - loss: 1.1573
- accuracy: 0.4378 - val_loss: 1.1648 - val_accuracy: 0.4381
Epoch 7/10
32398/32398 [==============================] - 1s 33us/step - loss: 1.1578
- accuracy: 0.4364 - val_loss: 1.1635 - val_accuracy: 0.4401
Epoch 8/10
32398/32398 [==============================] - 1s 34us/step - loss: 1.1577
- accuracy: 0.4362 - val_loss: 1.1637 - val_accuracy: 0.4401
Epoch 9/10
32398/32398 [==============================] - 1s 41us/step - loss: 1.1566
- accuracy: 0.4388 - val_loss: 1.1548 - val_accuracy: 0.4401
Epoch 10/10
32398/32398 [==============================] - 1s 35us/step - loss: 1.1567
- accuracy: 0.4387 - val_loss: 1.1685 - val_accuracy: 0.4354
```

In [69]:

```
score = model.score(X_test, y_test, verbose=0)
score
```

Out[69]:

```
0.43614813685417175
```

Conclusion

We conducted good EDA for YELP restaurant data and tested three different models to predict the star rating.

The best model in terms of stars prediction turned out to be neural network with test accuracy equal to 0.43.

Thus, we suggest our friends use this model to understand, how their current restaurant performance will behave in America and estimate their rating among clients.