In [2]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

In [3]:
```
import seaborn as sns
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
from sklearn import metrics
%matplotlib inline
```

In [4]:
```
train = pd.read_csv("train.csv")
meal = pd.read_csv("meal_info.csv")
center = pd.read_csv("fulfilment_center_info.csv")
```

In [5]:
```
df = pd.merge(train, meal, on=['meal_id', 'meal_id'])
df2 = pd.merge(df, center, on=['center_id', 'center_id'])
df2.head()
```

Out[5]:

	id	week	center_id	meal_id	checkout_price	base_price	emailer_for_promotion	homep
0	1379560	1	55	1885	136.83	152.29	0	
1	1018704	2	55	1885	135.83	152.29	0	
2	1196273	3	55	1885	132.92	133.92	0	
3	1116527	4	55	1885	135.86	134.86	0	
4	1343872	5	55	1885	146.50	147.50	0	

In [6]:
```
df2.to_csv(r'/Users/apple/Desktop/df2.csv', index = False)
```

In [7]:
```
from sklearn.preprocessing import LabelEncoder
class_le = LabelEncoder()
df2['center_type'] = class_le.fit_transform(df2['center_type'].values)
```

In [ ]:
```

```

In [8]:
```
#table = pd.pivot_table(df2, values=['checkout_price','num_orders'],inde
x=['cuisine'], aggfunc=np.mean)
#table.plot.bar()
```

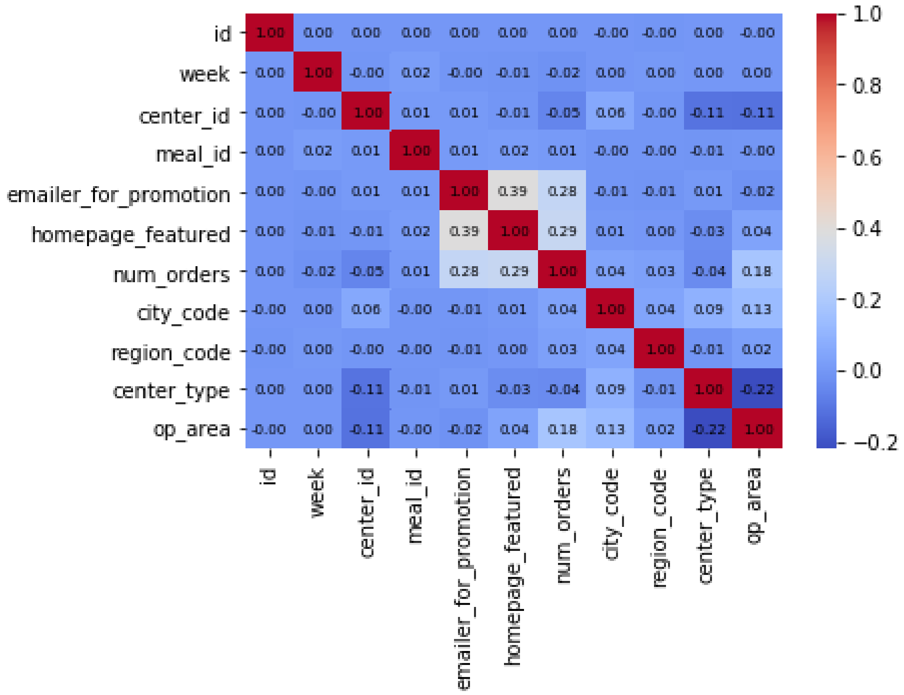
In [9]:
```
#df.plot(x='checkout_price', y='num_orders', style='o')
#plt.show()
```

In [10]:

```
df3 = df2.drop(['checkout_price','base_price'], axis=1)
sns.heatmap(df3.corr(),annot=True,fmt='.2f',cmap= 'coolwarm',annot_kws={
'size':7, 'color':'black'})
```

Out[10]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x10b86e7d0>
```



In [11]:

```
dummy_fields = ['center_type']

for each in dummy_fields:
    # get_dummies处理数据，参数prefix是指处理之后数据的前缀
    dummies = pd.get_dummies( center.loc[:, each], prefix=each )
    center = pd.concat( [center, dummies], axis = 1)
center.head()
```

Out[11]:

	center_id	city_code	region_code	center_type	op_area	center_type_TYPE_A	center_type_TYP
0	11	679	56	TYPE_A	3.7	1	
1	13	590	56	TYPE_B	6.7	0	
2	124	590	56	TYPE_C	4.0	0	
3	66	648	34	TYPE_A	4.1	1	
4	94	632	34	TYPE_C	3.6	0	

In [12]:

```
df2 = pd.merge(df, center, on=['center_id', 'center_id'])
df2.head()
```

Out[12]:

	id	week	center_id	meal_id	checkout_price	base_price	emailer_for_promotion	homep
0	1379560	1	55	1885	136.83	152.29	0	
1	1018704	2	55	1885	135.83	152.29	0	
2	1196273	3	55	1885	132.92	133.92	0	
3	1116527	4	55	1885	135.86	134.86	0	
4	1343872	5	55	1885	146.50	147.50	0	

In [13]:

```
df2['unit_checkoutprice']= df2['checkout_price'] / df2['num_orders']
df2['unit_baseprice'] = df2['base_price'] / df2['num_orders']
df2['price_pro'] = df2['unit_checkoutprice'] * df2['emailer_for_promotio
n']
#df2['price_center'] = df2['unit_price'] * df2['center_type']
#df2['price^2'] = df2['unit_price'] * df2['unit_price']
df2['price_feat'] = df2['unit_checkoutprice'] * df2['homepage_featured']
df2['log(order)'] = df2['num_orders'].apply(np.log)
df2.head()
```

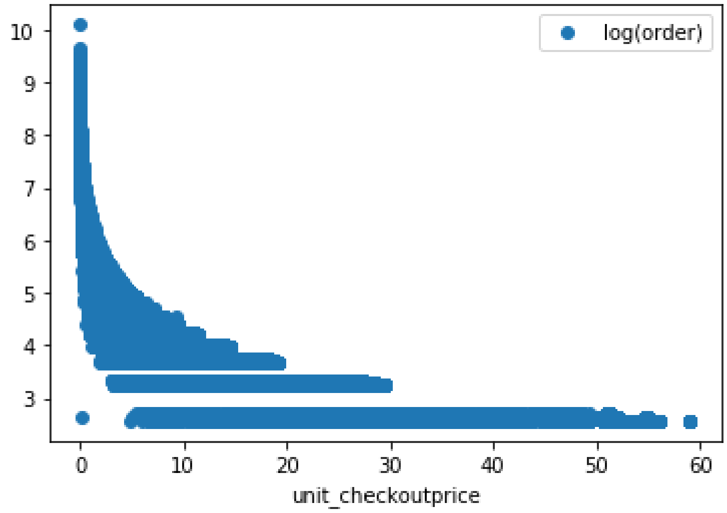
Out[13]:

	id	week	center_id	meal_id	checkout_price	base_price	emailer_for_promotion	homep
0	1379560	1	55	1885	136.83	152.29	0	
1	1018704	2	55	1885	135.83	152.29	0	
2	1196273	3	55	1885	132.92	133.92	0	
3	1116527	4	55	1885	135.86	134.86	0	
4	1343872	5	55	1885	146.50	147.50	0	

5 rows × 23 columns

In [14]:

```
df2.plot(x='unit_checkoutprice', y='log(order)', style='o')
plt.show()
```

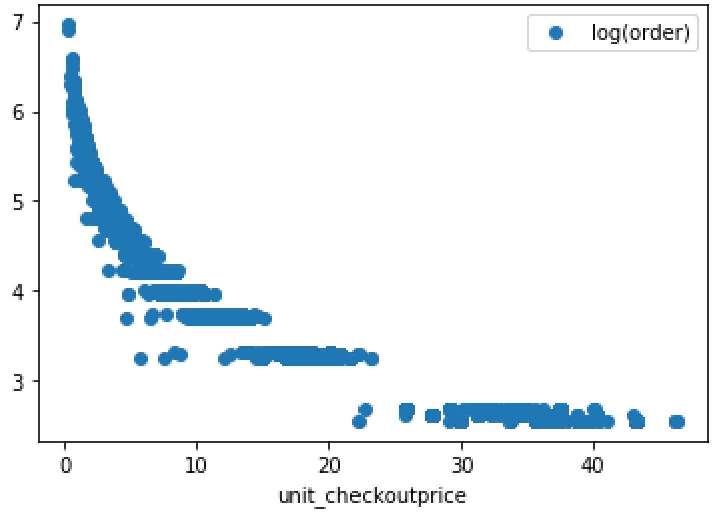


In [15]:

```
#food = ['1885','2707','2631','1230','2826,'1109','2569','2956','1962']
#for i in food:
meal = df2[df2['meal_id'].isin(['1543'])]
```

In [16]:

```
meal.plot(x='unit_checkoutprice', y='log(order)', style='o')
plt.show()
```



In [17]:

```
X1= meal[['unit_checkoutprice','emailer_for_promotion','homepage_feature
d','op_area','center_type_TYPE_A','center_type_TYPE_B','center_type_TYPE
_C']]
y1= meal['log(order)']
```

In [18]:

```python
import statsmodels.api as sm
X1 = sm.add_constant(X1)
est= sm.OLS(y1,X1).fit()
est.summary()
```

Out[18]:

```
OLS Regression Results

     Dep. Variable:         log(order)          R-squared:     0.842
             Model:                OLS      Adj. R-squared:     0.842
            Method:      Least Squares         F-statistic:     9097.
              Date:   Sun, 10 May 2020  Prob (F-statistic):      0.00
              Time:           23:07:35      Log-Likelihood:   -2747.5
 No. Observations:              10236                 AIC:     5509.
      Df Residuals:              10229                 BIC:     5560.
          Df Model:                  6
  Covariance Type:          nonrobust

                          coef  std err          t   P>|t|   [0.025   0.975]
                const   3.4151    0.012    295.277   0.000    3.392    3.438
    unit_checkoutprice -0.0681    0.000   -205.273   0.000   -0.069   -0.067
  emailer_for_promotion  0.2524    0.013     19.491   0.000    0.227    0.278
     homepage_featured   0.0524    0.009      5.571   0.000    0.034    0.071
               op_area   0.0647    0.003     19.138   0.000    0.058    0.071
      center_type_TYPE_A  1.0713    0.006    192.223   0.000    1.060    1.082
      center_type_TYPE_B  1.2456    0.008    151.650   0.000    1.230    1.262
      center_type_TYPE_C  1.0981    0.006    194.089   0.000    1.087    1.109

        Omnibus:  731.775      Durbin-Watson:      1.240
 Prob(Omnibus):    0.000   Jarque-Bera (JB):    913.092
           Skew:    0.675           Prob(JB):  5.30e-199
       Kurtosis:    3.563           Cond. No.   1.18e+17
```

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 1.74e-28. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

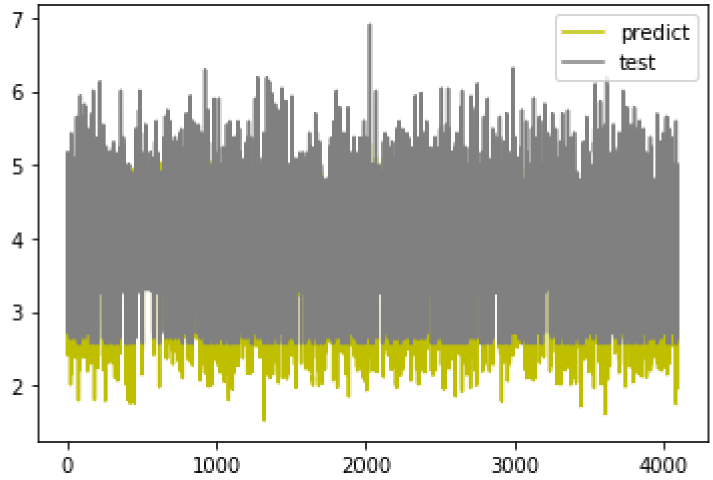
In [19]:

```
X1_train, X1_test, y1_train, y1_test =train_test_split(X1,y1, test_size=
0.4,random_state = 100)
meal = LinearRegression(fit_intercept=True)
meal.fit(X1_train,y1_train)
y1_pred = meal.predict(X1_test)
mse =mean_squared_error(y1_test, y1_pred)
print(mse)
```

```
0.10127333118949995
```

In [21]:

```
plt.figure()
plt.plot(range(len(y1_pred)),y1_pred,'y',label="predict")
plt.plot(range(len(y1_pred)),y1_test,'grey',label="test")
plt.legend(loc="upper right")
#plt.xlabel("the number of orders")
plt.show()
```



In [67]:

```
#cuisine = ['Thai','Italian','Indian','Continental']
cuisine = df2.loc[df2.cuisine.str.contains('Continental')]
category = df2.loc[df2.category.str.contains('Starters')]
```

In [68]:

```
import statsmodels.api as sm
X= category[['unit_checkoutprice','emailer_for_promotion','homepage_featured','op_area','center_type_TYPE_A','center_type_TYPE_B','center_type_TYPE_C']]
y= category['log(order)']
X = sm.add_constant(X)
est= sm.OLS(y,X).fit()
est.summary()
```

Out[68]:

```
OLS Regression Results

     Dep. Variable:         log(order)           R-squared:      0.815
            Model:                 OLS      Adj. R-squared:      0.815
           Method:       Least Squares          F-statistic:  2.195e+04
             Date:    Wed, 29 Apr 2020   Prob (F-statistic):       0.00
             Time:            22:35:14       Log-Likelihood:    -15111.
 No. Observations:               29941                  AIC:  3.024e+04
     Df Residuals:               29934                  BIC:  3.029e+04
         Df Model:                   6
  Covariance Type:           nonrobust

                          coef   std err        t   P>|t|   [0.025   0.975]
                const   3.6612     0.009  426.475   0.000    3.644    3.678
   unit_checkoutprice  -0.1390     0.001 -244.357   0.000   -0.140   -0.138
emailer_for_promotion   0.3699     0.012   30.914   0.000    0.346    0.393
    homepage_featured   0.2685     0.010   27.942   0.000    0.250    0.287
              op_area   0.0845     0.003   33.500   0.000    0.080    0.089
   center_type_TYPE_A   1.1633     0.004  296.386   0.000    1.156    1.171
   center_type_TYPE_B   1.5335     0.006  259.769   0.000    1.522    1.545
   center_type_TYPE_C   0.9644     0.005  178.960   0.000    0.954    0.975

       Omnibus:  1578.713       Durbin-Watson:     0.821
Prob(Omnibus):     0.000   Jarque-Bera (JB):  1837.760
          Skew:     0.600            Prob(JB):      0.00
      Kurtosis:     3.181           Cond. No.  2.64e+16


Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 2.17e-27. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
```