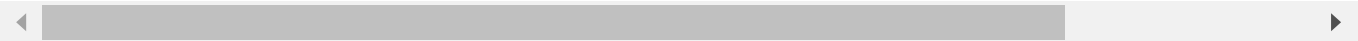



```
In [8]: df.head()
```

Out[8]:

	Quarter	CSUSHPINSA	NASDAQ100	Interest_rate	WPUSI012011	MORTGAGE30US	POPTHM	UNR/
0	2000 Q1	100.679000	4046.825397	127696	144.733333	8.256923	281304.333333	4.033
1	2000 Q2	103.698667	3629.497460	126924	145.166667	8.316154	282002.000000	3.933
2	2000 Q3	106.459000	3779.890000	139947	143.833333	8.020000	282768.666667	4.000
3	2000 Q4	108.270000	2941.222857	144433	142.833333	7.620769	283518.666667	3.900
4	2001 Q1	109.749333	2168.620952	143811	142.266667	7.006923	284168.666667	4.233



```
In [37]: df.rename(columns={'CSUSHPINSA': 'Index', 'WPUSI012011': 'cons_mat'}, inplace=True)
```

```
In [38]: df.shape
```

Out[38]: (90, 10)

```
In [39]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 90 entries, 0 to 89
Data columns (total 10 columns):
#   Column          Non-Null Count  Dtype
---  -
0   Quarter         90 non-null    object
1   Index           90 non-null    float64
2   NASDAQ100       90 non-null    float64
3   Interest_rate   90 non-null    int64
4   cons_mat        90 non-null    float64
5   MORTGAGE30US    90 non-null    float64
6   POPTHM          90 non-null    float64
7   UNRATE          90 non-null    float64
8   percapinc       90 non-null    int64
9   housunits       90 non-null    int64
dtypes: float64(6), int64(3), object(1)
memory usage: 7.7+ KB
```

```
In [40]: df.describe(include="all")
```

Out[40]:

	Quarter	Index	NASDAQ100	Interest_rate	cons_mat	MORTGAGE30US	POPTHM	L
count	90	90.000000	90.000000	90.000000	90.000000	90.000000	90.000000	90
unique	90	NaN	NaN	NaN	NaN	NaN	NaN	
top	2000 Q1	NaN	NaN	NaN	NaN	NaN	NaN	
freq	1	NaN	NaN	NaN	NaN	NaN	NaN	
mean	NaN	169.041648	4100.429369	216455.144444	200.884230	4.985707	310426.674074	5
std	NaN	41.061039	3610.055121	58960.683183	43.961087	1.359509	16100.877054	1
min	NaN	100.679000	945.332813	126924.000000	142.033333	2.760714	281304.333333	3
25%	NaN	141.962583	1633.297222	169301.500000	170.400000	3.887349	296526.666667	4
50%	NaN	165.653000	2588.831357	212705.500000	201.950000	4.717692	311658.333333	5
75%	NaN	184.360417	4814.456295	254024.000000	215.683333	6.084038	325399.333333	6
max	NaN	305.348000	15843.419219	360001.000000	348.737333	8.316154	332939.666667	12

```
In [42]: #Finding correlation
df.corr()['Index'].sort_values(ascending=False)
```

Out[42]:

Index	1.000000
Interest_rate	0.956532
cons_mat	0.896744
percapinc	0.877490
NASDAQ100	0.849974
housunits	0.814834
POPTHM	0.771812
UNRATE	-0.262429
MORTGAGE30US	-0.583233

Name: Index, dtype: float64

```
In [43]: #No missing values
df.isnull().sum()
```

Out[43]:

Quarter	0
Index	0
NASDAQ100	0
Interest_rate	0
cons_mat	0
MORTGAGE30US	0
POPTHM	0
UNRATE	0
percapinc	0
housunits	0

dtype: int64

```
In [44]: df.to_excel('data/data.xlsx',index=False)
```

```
In [46]: x=df.drop(["Index","Quarter"],axis=True)
y=df["Index"]
```

```
In [56]: from sklearn.ensemble import RandomForestRegressor
import matplotlib.pyplot as plt
```

```
In [48]: #training random forest model
reg = RandomForestRegressor(n_estimators=100)
reg.fit(x,y)
```

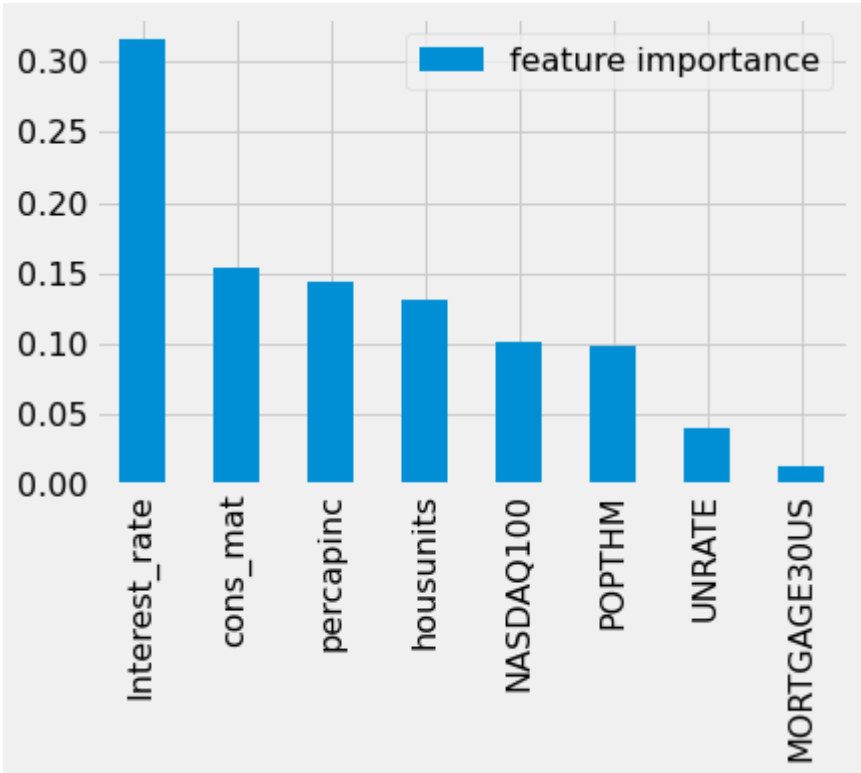
Out[48]: RandomForestRegressor()

```
In [49]: #feature importance
df_feature_importance = pd.DataFrame(reg.feature_importances_, index=x.columns, columns=['importance'])
df_feature_importance
```

Out[49]:

feature importance	
Interest_rate	0.315570
cons_mat	0.153915
percapinc	0.144698
housunits	0.131795
NASDAQ100	0.101607
POPTHM	0.098465
UNRATE	0.040440
MORTGAGE30US	0.013510

```
In [50]: df_feature_importance.plot(kind='bar');
```



```
In [51]: #training xgboost regressor
import xgboost as xgb
from sklearn.model_selection import GridSearchCV
```

```
In [52]: xgbregressor=xgb.XGBRegressor(eval_metric='rmsle')
```

```
In [53]: param_grid = {"max_depth":    [4, 5],
                      "n_estimators": [500, 600, 700],
                      "learning_rate": [0.01, 0.015]}

# try out every combination of the above values
search = GridSearchCV(xgbregressor, param_grid, cv=5).fit(x,y)

print("The best hyperparameters are ",search.best_params_)
```

The best hyperparameters are {'learning_rate': 0.015, 'max_depth': 4, 'n_estimators': 600}

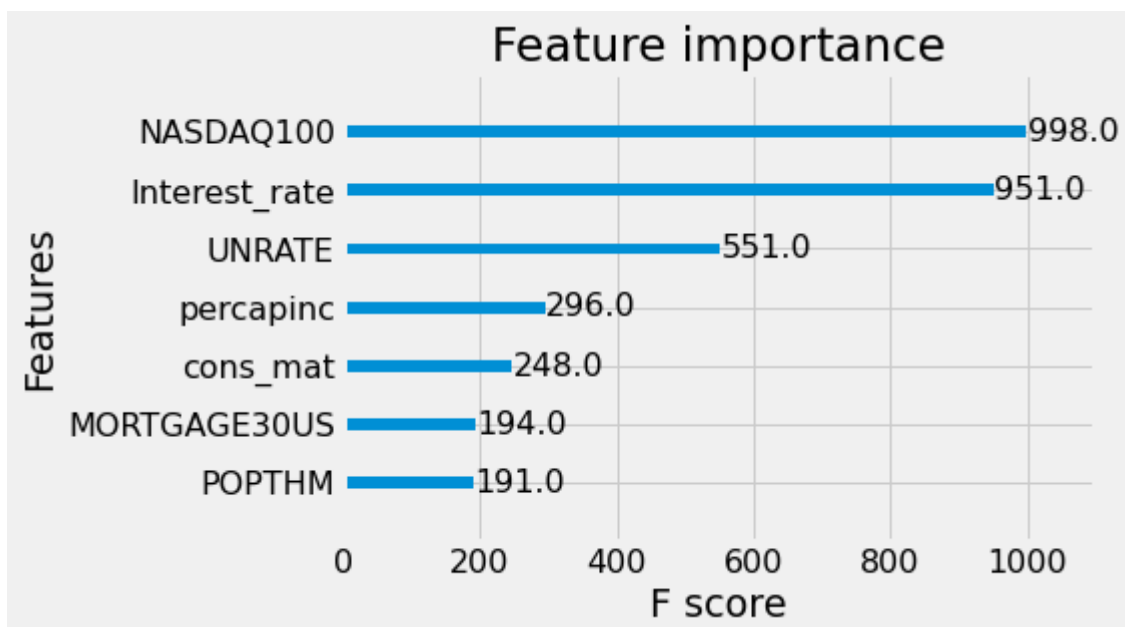
```
In [54]: xgbregressor=xgb.XGBRegressor(learning_rate = search.best_params_["learning_rate"],
                                       n_estimators = search.best_params_["n_estimators"],
                                       max_depth     = search.best_params_["max_depth"],
                                       eval_metric='rmsle')

xgbregressor.fit(x,y)
```

```
Out[54]: XGBRegressor(base_score=0.5, booster='gbtree', callbacks=None,
                      colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1,
                      early_stopping_rounds=None, enable_categorical=False,
                      eval_metric='rmsle', gamma=0, gpu_id=-1, grow_policy='depthwise',
                      importance_type=None, interaction_constraints='',
                      learning_rate=0.015, max_bin=256, max_cat_to_onehot=4,
                      max_delta_step=0, max_depth=4, max_leaves=0, min_child_weight=1,
                      missing=nan, monotone_constraints='()', n_estimators=600, n_jobs=0,
                      num_parallel_tree=1, predictor='auto', random_state=0, reg_alpha=0,
                      reg_lambda=1, ...)
```

```
In [55]: from xgboost import plot_importance
import matplotlib.pyplot as plt
```

```
plot_importance(xgbregressor)
plt.show()
```



In []: