In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.feature_selection import RFE
from sklearn import preprocessing

df = pd.read_csv("cereal_cleaned.csv")
```

In [2]:
```
df.head()
```

Out[2]:

	Unnamed: 0	name	manufacturer	type	calories	protein	fat	sodium	fiber	carbo	sugars	po
0	0	100% Bran	Nabisco	Cold	70	4	1	130	10.0	5.0	6.0	2
1	1	100% Natural Bran	Quaker	Cold	120	3	5	15	2.0	8.0	8.0	1
2	2	All-Bran	Kellogs	Cold	70	4	1	260	9.0	7.0	5.0	3
3	3	All-Bran with Extra Fiber	Kellogs	Cold	50	4	0	140	14.0	8.0	0.0	3
4	4	Almond Delight	Ralston Purina	Cold	110	2	2	200	1.0	14.0	8.0	

In [3]:
```
df= df.dropna()
```

Feature Selection

We removed "manufacturer" because we were more interested in the components of the cereal rather than the brand of the cereal. We also removed "type" because there are only three hot cereals in our dataset.

In [4]:
```
df_X = df[["calories", "protein", "fat", "sodium", "fiber", "carbo", "sugars", "p
df_y = df["rating"]
```

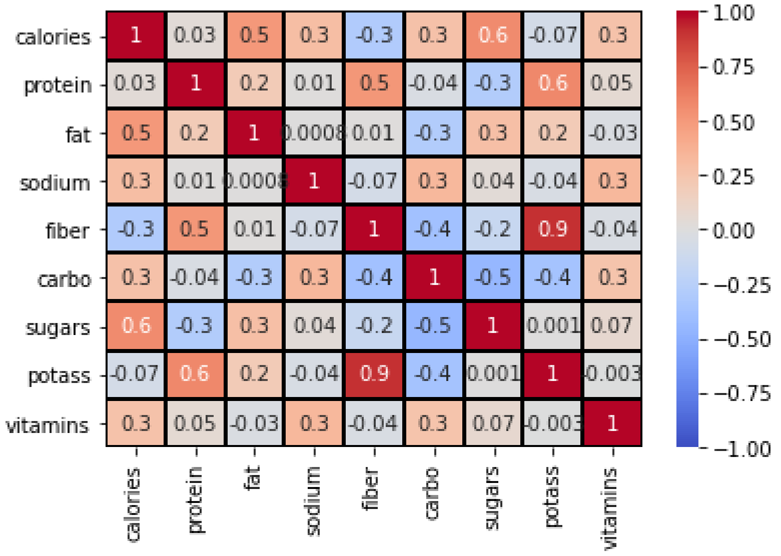
Normalize the data

In [5]:
```
min_max_scaler = preprocessing.MinMaxScaler()
norm_X = pd.DataFrame(min_max_scaler.fit_transform(df_X.values), columns = df_X.c
```

Our correlation heatmap shows that potassium is highly correlated with fiber (0.9) so we removed the potassium feature

In [6]:
```
sns.heatmap(norm_X.corr(), annot = True, fmt='.1g', vmin=-1, vmax=1, center= 0,
            cmap= 'coolwarm', linewidths=1, linecolor='black')
```

Out[6]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x163c792f408>
```



	calories	protein	fat	sodium	fiber	carbo	sugars	potass	vitamins
calories	1	0.03	0.5	0.3	-0.3	0.3	0.6	-0.07	0.3
protein	0.03	1	0.2	0.01	0.5	-0.04	-0.3	0.6	0.05
fat	0.5	0.2	1	0.0008	0.01	-0.3	0.3	0.2	-0.03
sodium	0.3	0.01	0.0008	1	-0.07	0.3	0.04	-0.04	0.3
fiber	-0.3	0.5	0.01	-0.07	1	-0.4	-0.2	0.9	-0.04
carbo	0.3	-0.04	-0.3	0.3	-0.4	1	-0.5	-0.4	0.3
sugars	0.6	-0.3	0.3	0.04	-0.2	-0.5	1	0.001	0.07
potass	-0.07	0.6	0.2	-0.04	0.9	-0.4	0.001	1	-0.003
vitamins	0.3	0.05	-0.03	0.3	-0.04	0.3	0.07	-0.003	1

In [7]:
```
norm_X.drop("potass", axis=1, inplace = True)
```

Here we use RFE (Recursive Feature Elimination) for selecting features. RFE removes attributes and builds the regression to rank features. The output are the features rankings.

In [8]:
```
model = LinearRegression()
#Initializing RFE model
rfe = RFE(model, 1)
#Transforming data using RFE
X_rfe = rfe.fit_transform(norm_X,df_y)
#Fitting the data to model
model.fit(X_rfe,df_y)
print(rfe.ranking_)
```

```
[1 5 7 4 2 3 6 8]
```

Below we used these ranked features and and create models with one feature and the way to eight features. Each model is scored the highest score tells us the number of features we should move forward with.

In [9]:
```
# number of features that we are choosing from
nof_list=np.arange(1,8)
# variable to store the high score
high_score=0

# variable to store the optimum features
nof=0
score_list =[]

# loop through
for n in range(len(nof_list)):
    X_train, X_test, y_train, y_test = train_test_split(norm_X,df_y, test_size =
    model = LinearRegression()
    rfe = RFE(model,nof_list[n])
    X_train_rfe = rfe.fit_transform(X_train,y_train)
    X_test_rfe = rfe.transform(X_test)
    model.fit(X_train_rfe,y_train)
    score = model.score(X_test_rfe,y_test)
    score_list.append(score)
    if(score>high_score):
        high_score = score
        nof = nof_list[n]
print("Optimum number of features: %d" %nof)
print("Score with %d features: %f" % (nof, high_score))
```

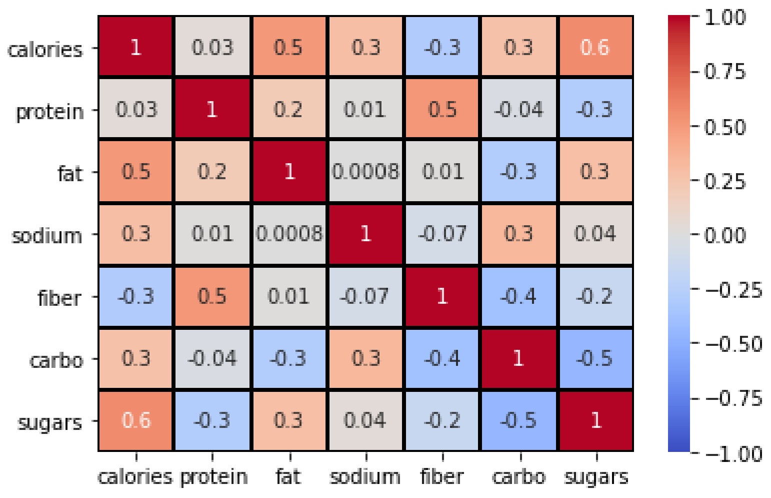
```
Optimum number of features: 7
Score with 7 features: 0.989774
```

Because 7 features are shown as optimum we can remove the worst performing feature which was vitamins.

In [10]:
```
norm_X.drop("vitamins", axis=1, inplace = True)
```

In [11]:
```
sns.heatmap(norm_X.corr(), annot = True, fmt='.1g', vmin=-1, vmax=1, center= 0,
            cmap= 'coolwarm', linewidths=1, linecolor='black')
```

Out[11]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x163e2ada408>
```

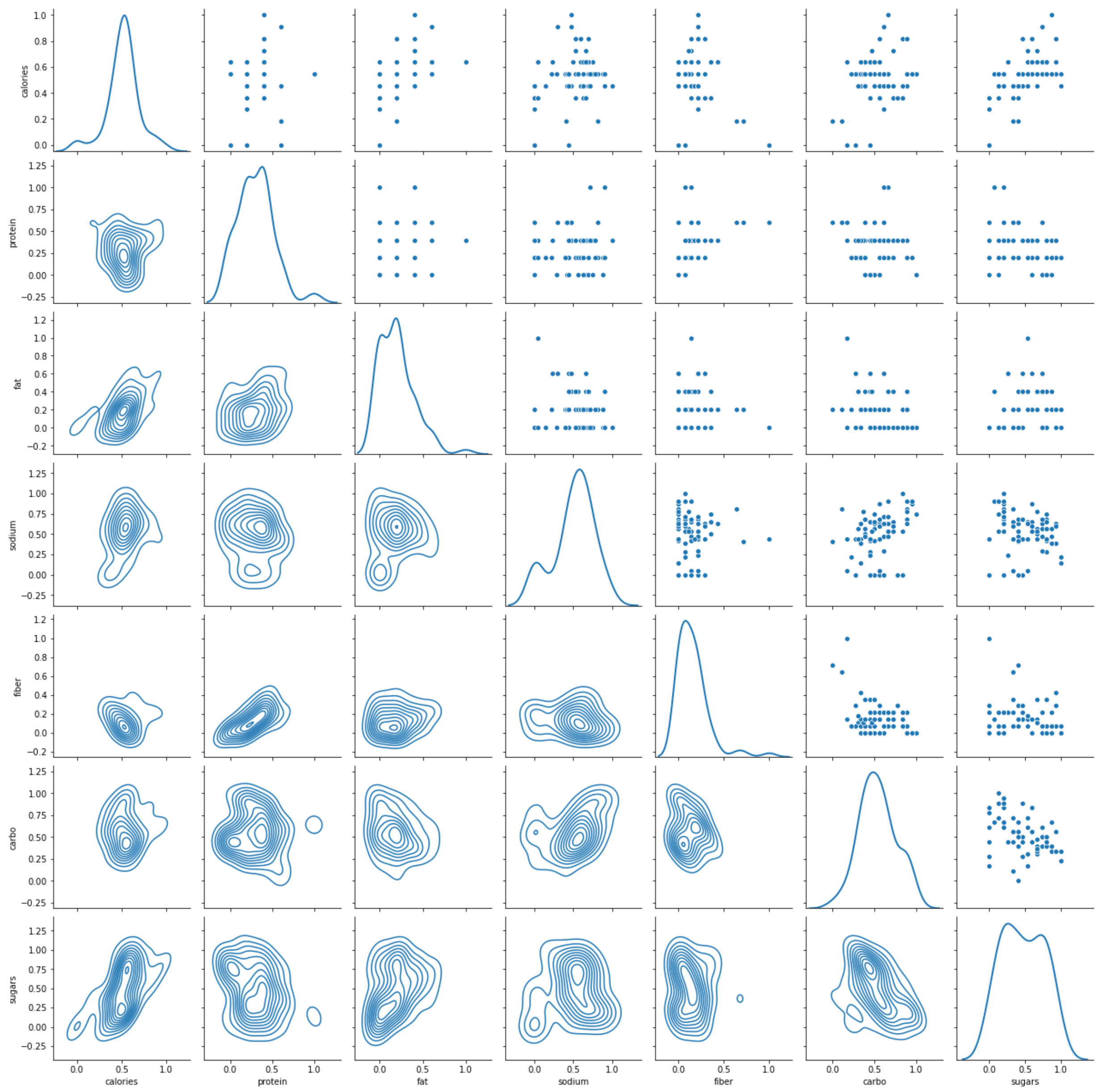


	calories	protein	fat	sodium	fiber	carbo	sugars
calories	1	0.03	0.5	0.3	-0.3	0.3	0.6
protein	0.03	1	0.2	0.01	0.5	-0.04	-0.3
fat	0.5	0.2	1	0.0008	0.01	-0.3	0.3
sodium	0.3	0.01	0.0008	1	-0.07	0.3	0.04
fiber	-0.3	0.5	0.01	-0.07	1	-0.4	-0.2
carbo	0.3	-0.04	-0.3	0.3	-0.4	1	-0.5
sugars	0.6	-0.3	0.3	0.04	-0.2	-0.5	1

Pair Grid

```
In [12]: g = sns.PairGrid(norm_X, diag_sharey=False)
         g.map_upper(sns.scatterplot)
         g.map_lower(sns.kdeplot, colors="C0")
         g.map_diag(sns.kdeplot, lw=2)
```

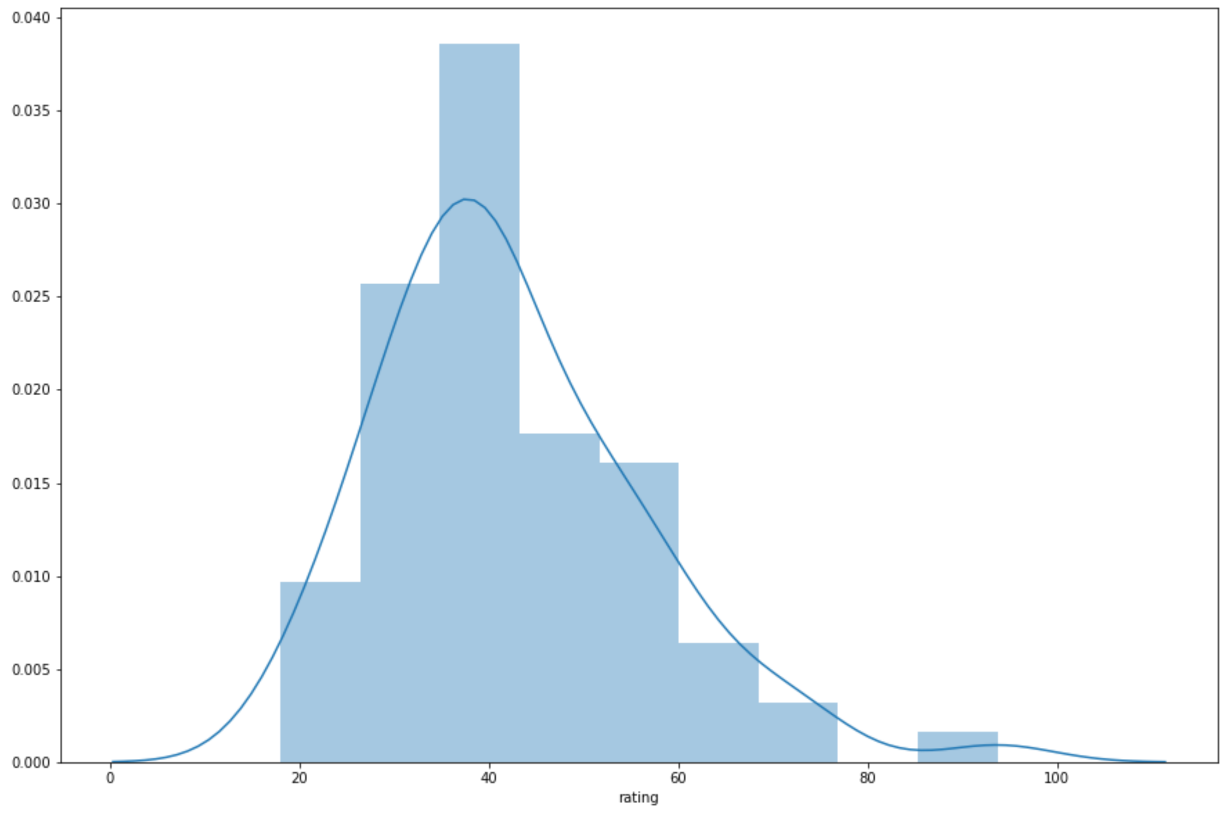
```
Out[12]: <seaborn.axisgrid.PairGrid at 0x163e4e63e48>
```



Distribution of ratings

In [13]:
```
plt.figure(figsize=(15,10))
plt.tight_layout()
sns.distplot(df_y)
```

Out[13]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x163e7a3c8c8>
```



Linear Regression

We will be performing linear regression on our selected variable to determine which features have the most impact to the cereals ratings.

In [14]:
```
X_train, X_test, y_train, y_test = train_test_split(norm_X,df_y, test_size = 0.3,

regressor = LinearRegression()
regressor.fit(X_train, y_train)
```

Out[14]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

In [15]:
```
from sklearn import metrics
y_pred = regressor.predict(X_test)
```

This model has a very high R-squared so the model accurately explains the variation in rating

In [16]:
```
from sklearn.metrics import r2_score
r2_score(y_test, y_pred)
```

Out[16]:
```
0.9897744614968232
```

In [17]:
```
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test, y_pr
```

```
Mean Absolute Error: 1.0047905961895693
Mean Squared Error: 1.6773176179583091
Root Mean Squared Error: 1.2951129749787502
```

In [18]:
```
coeff_df = pd.DataFrame(regressor.coef_, norm_X.columns, columns=['Coefficient'])
coeff_df
```

Out[18]:

	Coefficient
calories	-20.136033
protein	13.276032
fat	-11.930712
sodium	-17.760929
fiber	33.858466
carbo	12.840273
sugars	-16.953433

This shows that calories, fat, sodium, and sugar had a negative impact to rating while carbs, fiber, and protein had a positive impact to rating.

In [ ]: