Visualization

```
In [0]:
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import sys
import seaborn as sns

In [0]:

df = pd.read_csv("pokemon_alopez247.csv", sep=",")

In [3]:

In [4]:

In [5]:

In [
```

There are 23 columns:

Number, Name, Type_1, Type_2, Total, HP, Attack, Defense, Sp_Atk, Sp_Def, Speed, Gen eration, isLegendary, Color, hasGender, Pr_Male, Egg_Group_1, Egg_Group_2, hasMegaEv olution, Height_m, Weight_kg, Catch_Rate, Body_Style,

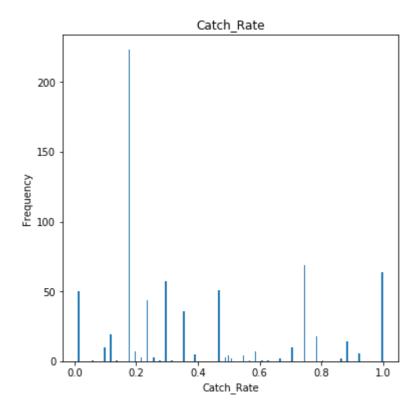
In [4]:

```
fig, ax = plt.subplots(figsize=(15, 15))
sns.heatmap(df.corr(), ax=ax, annot=True, linewidths=0.05, fmt='.2f', cmap="magma")
plt.show()
```

Number :	1.00	0.16	0.11	0.14	0.12	0.12	0.11	0.03	0.98	0.14	-0.10	-0.01	-0.12	-0.01	0.09	-0.07		- 0.9
Total ·	0.16	1.00	0.64	0.70	0.61	0.72	0.71	0.55	0.09	0.48	-0.39	0.11	0.23	0.53	0.54	-0.74		- 0.9
HP ·	0.11	0.64	1.00	0.43	0.23	0.37	0.38	0.17	0.07	0.26	-0.16	-0.07	0.09	0.44	0.43	-0.48		
Attack ·	0.14	0.70	0.43	1.00	0.43	0.34	0.21	0.34	0.09	0.30	-0.20	0.21	0.20	0.41	0.47	-0.53		- 0.6
Defense :	0.12	0.61	0.23	0.43	1.00	0.20	0.48	-0.01	0.07	0.27	-0.27	0.06	0.12	0.35	0.48	-0.44		
Sp_Atk	0.12	0.72	0.37	0.34	0.20	1.00	0.49	0.44	0.07	0.41	-0.34	0.11	0.18	0.33	0.29	-0.54		
Sp_Def	0.11	0.71	0.38	0.21		0.49	1.00	0.23	0.06	0.36	-0.34	0.02	0.15	0.31	0.33	-0.51		- 0.3
Speed ·	0.03	0.55	0.17	0.34	-0.01	0.44	0.23	1.00	0.00	0.29	-0.22	0.07	0.15	0.22	0.11	-0.41		
Generation ·	0.98	0.09	0.07	0.09	0.07	0.07	0.06	0.00	1.00	0.07	-0.03	0.01	-0.13	-0.05	0.03	-0.03		
isLegendary ·	0.14	0.48	0.26	0.30	0.27	0.41	0.36	0.29	0.07	1.00	-0.64	0.10	0.05	0.33	0.43	-0.32		- 0.0
hasGender ·	-0.10	-0.39	-0.16	-0.20	-0.27	-0.34	-0.34	-0.22	-0.03	-0.64	1.00		0.02	-0.20	-0.36	0.27		
Pr_Male	-0.01	0.11	-0.07	0.21	0.06	0.11	0.02	0.07	0.01	0.10		1.00	0.03	0.04	0.06	-0.25		0.3
hasMegaEvolution	-0.12	0.23	0.09	0.20	0.12	0.18	0.15	0.15	-0.13	0.05	0.02	0.03	1.00	0.19	0.13	-0.17		0.5
Height_m	-0.01	0.53	0.44	0.41	0.35	0.33	0.31	0.22	-0.05	0.33	-0.20	0.04	0.19	1.00	0.66	-0.38		
Weight_kg	0.09	0.54	0.43	0.47	0.48	0.29	0.33	0.11	0.03	0.43	-0.36	0.06	0.13	0.66	1.00	-0.37		0.6
Catch_Rate	-0.07	-0.74	-0.48	-0.53	-0.44	-0.54	-0.51	-0.41	-0.03	-0.32	0.27	-0.25	-0.17	-0.38	-0.37	1.00		
	Number -	Total -	- H	Attack -	Defense -	Sp_Atk -	Sp_Def -	- Speed -	Generation -	isLegendary -	hasGender -	Pr_Male -	hasMegaEvolution -	Height_m -	Weight_kg -	Catch_Rate -		

In [5]:

```
Catch_Rate = df["Catch_Rate"]
Catch_Rate_ = Catch_Rate/255
Catch_Rate_.plot(kind='hist', bins=200, figsize=(6, 6))
plt.title("Catch_Rate")
plt.xlabel("Catch_Rate")
plt.ylabel("Frequency")
plt.show()
```



```
In [6]:
```

```
number = df["Number"]
print('Total number of Pokemons is', len(number))
Legendary = df["isLegendary"]
rate = np. mean(Legendary == True)
print('legendary rate=', rate)
```

Total number of Pokemons is 721 legendary rate= 0.0638002773925104 In [0]:

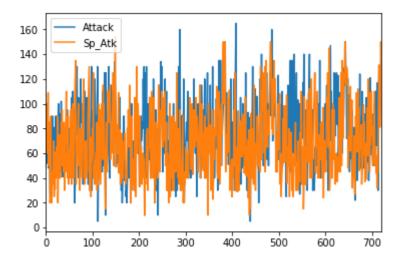
```
# Unnecessary columns
# Number and Name are just identifiers
# Total is a aggregation of others columns
clean_df = df.drop(columns=['Number', 'Name', 'Total'])
```

```
In [8]:
```

```
df2 = df. loc[:, ["Attack", "Sp_Atk"]]
df2.plot()
```

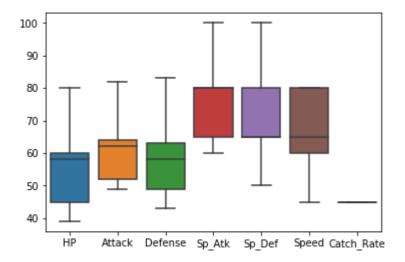
Out[8]:

 $\label{lib.axes.subplots.AxesSubplot} $$\operatorname{at\ Ox7fd6f6e2b5f8}$$$



In [9]:

Out[9]: <function matplotlib.pyplot.show>



In [10]:

```
fig, axes = plt.subplots(nrows=2, ncols=1)
df.plot(kind="hist", y="Catch_Rate", bins=50, range=(0, 255), normed=True, ax=axes[0])
df.plot(kind="hist", y="Catch_Rate", bins=50, range=(0, 255), normed=True, ax=axes[1], cumulative=
plt.show()
# there's a sudden increase around 0.16 percentage of Catch_Rate
```

/usr/local/lib/python3.6/dist-packages/matplotlib/axes/_axes.py:6521: MatplotlibDeprecationWarning:

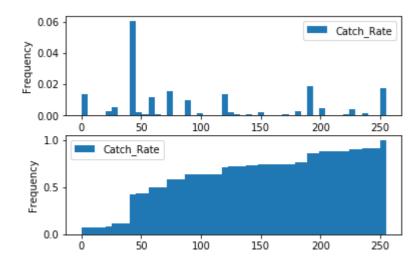
The 'normed' kwarg was deprecated in Matplotlib 2.1 and will be removed in 3.1. Use 'density' instead.

alternative="'density'", removal="3.1")

/usr/local/lib/python3.6/dist-packages/matplotlib/axes/_axes.py:6521: MatplotlibDeprecationWarning:

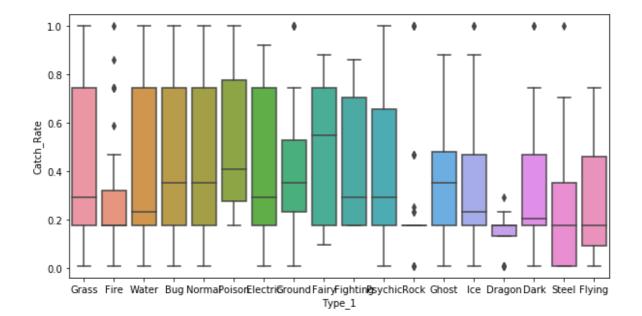
The 'normed' kwarg was deprecated in Matplotlib 2.1 and will be removed in 3.1. Use 'density' instead.

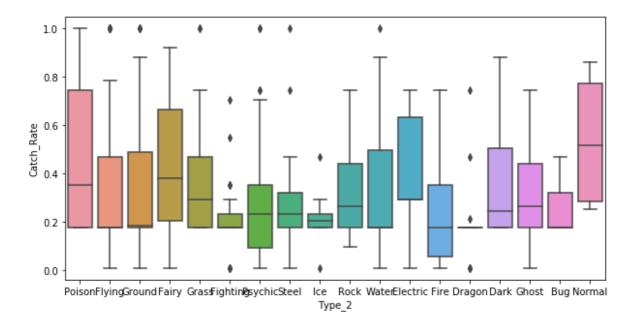
alternative="'density'", removal="3.1")



In [11]:

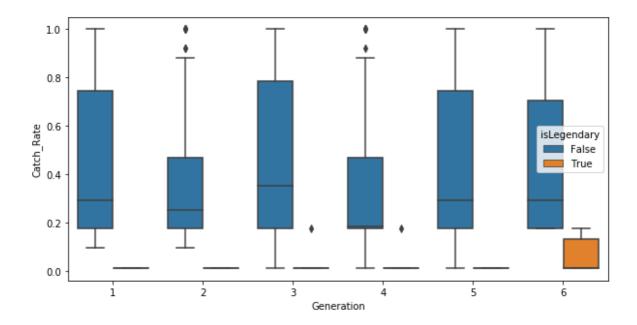
```
plt.figure(figsize=(10, 5))
ax = sns.boxplot(x='Type_1', y=Catch_Rate_, data=df)
plt.figure(figsize=(10, 5))
ax = sns.boxplot(x='Type_2', y=Catch_Rate_, data=df)
```





In [12]:

```
# If generation and islegendary relate to Catch_rate
plt.figure(figsize=(10, 5))
ax = sns.boxplot(x='Generation', y=Catch_Rate_, hue='isLegendary', data=df)
```



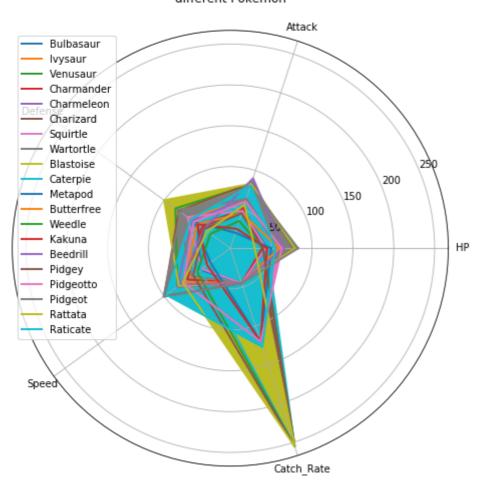
In [13]:

	Name	HP	Attack	Defense	Speed	Catch_Rate
0	Bulbasaur	45	49	49	45	45
1	Ivysaur	60	62	63	60	45
2	Venusaur	80	82	83	80	45
3	Charmander	39	52	43	65	45
4	Charmeleon	58	64	58	80	45
5	Charizard	78	84	78	100	45
6	Squirtle	44	48	65	43	45
7	Wartortle	59	63	80	58	45
8	Blastoise	79	83	100	78	45
9	Caterpie	45	30	35	45	255
10	Metapod	50	20	55	30	120
11	Butterfree	60	45	50	70	45
12	Weedle	40	35	30	50	255
13	Kakuna	45	25	50	35	120
14	Beedrill	65	90	40	75	45
15	Pidgey	40	45	40	56	255
16	Pidgeotto	63	60	55	71	120
17	Pidgeot	83	80	75	101	45
18	Rattata	30	56	35	72	255
19	Raticate	55	81	60	97	127

In [14]: ▶

```
def result pic(result):
    labels = ['HP', 'Attack', 'Defense', 'Speed', 'Catch_Rate']
   kinds = list(result.iloc[:, 0])
   result = pd.concat([result, result[['HP']]], axis=1)
   centers = np. array(result.iloc[:, 1:])
   n = len(labels)
   angle = np.linspace(0, 2 * np.pi, n, endpoint=False)
    angle = np. concatenate((angle, [angle[0]]))
    fig = plt.figure(figsize=(8, 8))
   ax = fig.add_subplot(111, polar=True)
    for i in range (len(kinds)):
        ax.plot(angle, centers[i], linewidth=2, label=kinds[i])
        ax.fill(angle, centers[i])
    ax.set_thetagrids(angle * 180 / np.pi, labels)
    plt. title('different Pokemon')
    plt.legend(loc='upper left')
    plt.show()
if __name__ == '__main__':
   result = result1
   result_pic(result)
```

different Pokemon



In [15]:

```
/usr/local/lib/python3.6/dist-packages/numpy/core/_methods.py:140: RuntimeWarning: D egrees of freedom <= 0 for slice keepdims=keepdims)
/usr/local/lib/python3.6/dist-packages/numpy/core/_methods.py:132: RuntimeWarning: i
```

/usr/local/lib/python3.6/dist-packages/numpy/core/_methods.py:132: RuntimeWarning: invalid value encountered in double_scalars

ret = ret.dtype.type(ret / rcount)

/usr/local/lib/python3.6/dist-packages/statsmodels/nonparametric/kde.py:488: Runtime Warning: invalid value encountered in true_divide

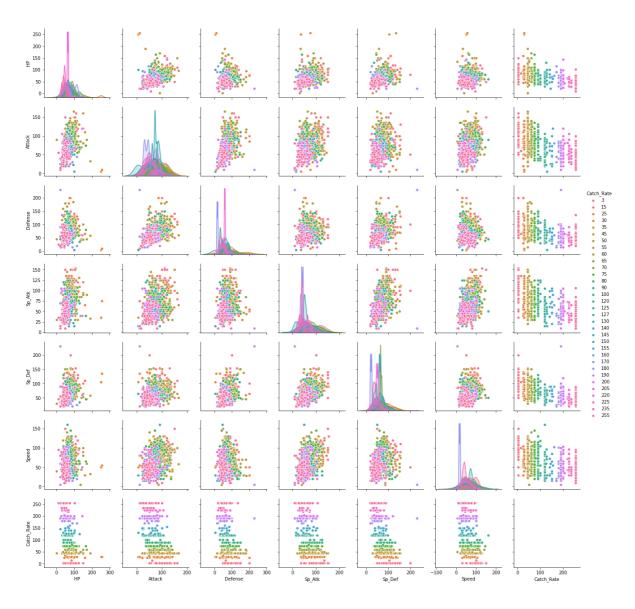
binned = fast_linbin(X, a, b, gridsize) / (delta * nobs)

/usr/local/lib/python3.6/dist-packages/statsmodels/nonparametric/kdetools.py:34: Run timeWarning: invalid value encountered in double_scalars

FAC1 = 2*(np. pi*bw/RANGE)**2

Out[15]:

<function matplotlib.pyplot.show>



```
In [16]:
```

```
df.describe()
```

Out[16]:

	Number	Total	HP	Attack	Defense	Sp_Atk	Sp_Def	
count	721.00000	721.000000	721.000000	721.000000	721.000000	721.000000	721.000000	721
mean	361.00000	417.945908	68.380028	75.013870	70.808599	68.737864	69.291262	65
std	208.27906	109.663671	25.848272	28.984475	29.296558	28.788005	27.015860	27
min	1.00000	180.000000	1.000000	5.000000	5.000000	10.000000	20.000000	5
25%	181.00000	320.000000	50.000000	53.000000	50.000000	45.000000	50.000000	45
50%	361.00000	424.000000	65.000000	74.000000	65.000000	65.000000	65.000000	65
75%	541.00000	499.000000	80.000000	95.000000	85.000000	90.000000	85.000000	85
max	721.00000	720.000000	255.000000	165.000000	230.000000	154.000000	230.000000	160

```
In [0]:
```

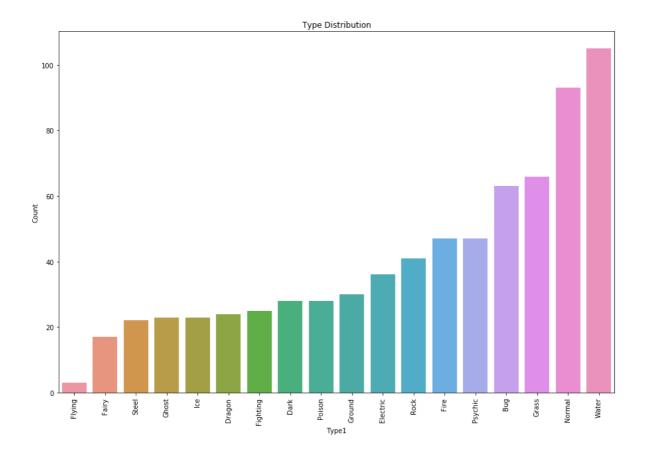
```
df1 = df.groupby('Type_1')['Type_1'].count().reset_index(name='Count')
df1 = df1.sort_values(by='Count')
```

In [18]:

```
plt.figure(figsize=(15, 10))
sns.barplot(x=df1['Type_1'], y=df1['Count'])
plt.xticks(rotation=90)
plt.xlabel('Type1')
plt.ylabel('Count')
plt.title('Type Distribution')
```

Out[18]:

Text(0.5, 1.0, 'Type Distribution')



```
In [0]:

df2 = df. groupby('Type_2')['Type_2']. count(). reset_index(name='Count')

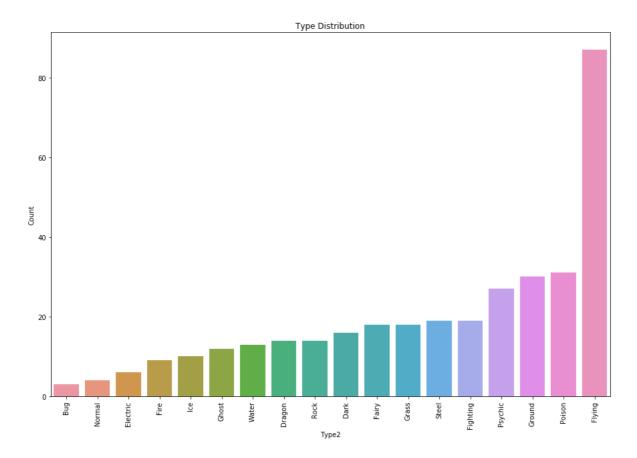
df2 = df2. sort_values(by='Count')
```

In [20]:

```
plt.figure(figsize=(15, 10))
sns.barplot(x=df2['Type_2'], y=df2['Count'])
plt.xticks(rotation=90)
plt.xlabel('Type2')
plt.ylabel('Count')
plt.title('Type Distribution')
```

Out[20]:

Text(0.5, 1.0, 'Type Distribution')

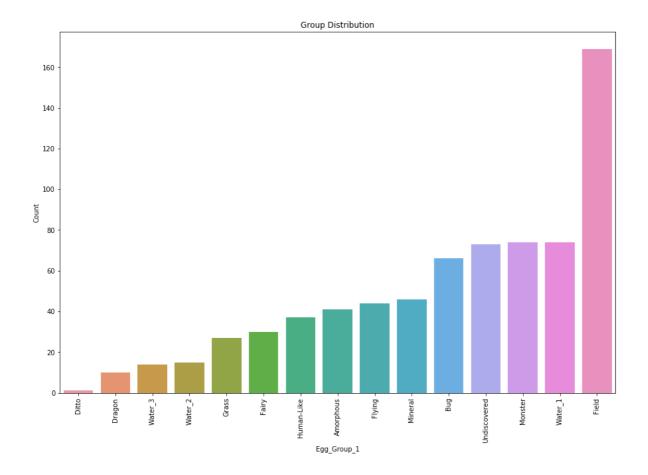


In [21]:

```
df3 = df.groupby('Egg_Group_1')['Egg_Group_1'].count().reset_index(name='Count')
df3 = df3.sort_values(by='Count')
plt.figure(figsize=(15, 10))
sns.barplot(x=df3['Egg_Group_1'], y=df3['Count'])
plt.xticks(rotation=90)
plt.xlabel('Egg_Group_1')
plt.ylabel('Count')
plt.title('Group Distribution')
```

Out[21]:

Text(0.5, 1.0, 'Group Distribution')

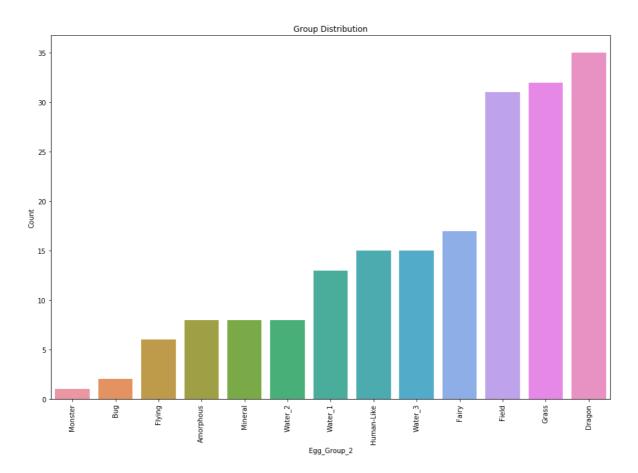


In [22]:

```
df4 = df. groupby('Egg_Group_2')['Egg_Group_2'].count().reset_index(name='Count')
df4 = df4.sort_values(by='Count')
plt.figure(figsize=(15, 10))
sns.barplot(x=df4['Egg_Group_2'], y=df4['Count'])
plt.xticks(rotation=90)
plt.xlabel('Egg_Group_2')
plt.ylabel('Count')
plt.title('Group Distribution')
```

Out[22]:

Text(0.5, 1.0, 'Group Distribution')



In [0]:

```
import sys
import os
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
import sklearn
from sklearn.linear_model import LinearRegression, Ridge, Lasso
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import r2_score
from sklearn.model_selection import train_test_split, KFold
from sklearn.decomposition import PCA
import torch
import torch.nn.functional as F
import torch.nn as nn
import torch.utils.data as utils
```

```
In [0]:
```

```
df = pd.read_csv("pokemon_alopez247.csv", sep=",")
```

In [25]:

```
print(df.head(6))
print(df.info())
```

```
Number
                 Name Type_1 ... Weight_kg Catch_Rate
                                                               Body_Style
0
            Bulbasaur
                      Grass
                                                                quadruped
        1
                              . . .
                                         6.9
        2
              Ivysaur
                                        13.0
                                                       45
1
                       Grass
                                                                quadruped
2
        3
             Venusaur
                       Grass
                                       100.0
                                                       45
                                                                quadruped
                              . . .
3
        4
                                                       45
          Charmander
                        Fire ...
                                         8.5
                                                          bipedal tailed
        5
           Charmeleon
4
                        Fire ...
                                        19.0
                                                       45
                                                           bipedal tailed
5
        6
            Charizard
                        Fire ...
                                        90.5
                                                       45
                                                           bipedal tailed
[6 rows x 23 columns]
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 721 entries, 0 to 720
Data columns (total 23 columns):
Number
                    721 non-null int64
Name
                     721 non-null object
                     721 non-null object
Type_1
Type_2
                     350 non-null object
Total
                     721 non-null int64
                     721 non-null int64
HP
Attack
                     721 non-null int64
Defense
                    721 non-null int64
Sp_Atk
                     721 non-null int64
Sp_Def
                     721 non-null int64
                     721 non-null int64
Speed
Generation
                     721 non-null int64
                     721 non-null bool
isLegendary
Color
                     721 non-null object
                     721 non-null bool
hasGender
Pr_Male
                     644 non-null float64
Egg Group 1
                     721 non-null object
Egg_Group_2
                     191 non-null object
hasMegaEvolution
                    721 non-null bool
                     721 non-null float64
Height m
Weight kg
                     721 non-null float64
```

dtypes: bool(3), float64(3), int64(10), object(7)

721 non-null int64 721 non-null object

memory usage: 114.8+ KB

None

Catch Rate

Body Style

Prediction

1. Data preprocessed

Convert text labels to one hot code.

选择one hot的原因 Reason (http://queirozf.com/entries/one-hot-encoding-a-feature-on-a-pandas-dataframe-an-example)

In [0]:

```
df1 = df.copy()

df1 = pd.get_dummies(data=df1, columns=['Type_1', 'Type_2'], prefix='Type')

df1 = pd.get_dummies(data=df1, columns=['Color'], prefix='Color')

df1 = pd.get_dummies(data=df1, columns=['Egg_Group_1', 'Egg_Group_2'], prefix='Egg_Group')

df1 = pd.get_dummies(data=df1, columns=['Body_Style'], prefix='Body_Style')

df1 = df1.fillna(0)
```

Generate X and y from the dataset.

```
In [27]:

# X = df1. loc[:, df1. columns != 'Name']
```

```
# X = df1.loc[:, df1.columns != 'Name']
X = df1.drop(['Name', 'Number', 'Catch_Rate'], axis=1).to_numpy().astype(float)
labels = df1.drop(['Name', 'Number', 'Catch_Rate'], axis=1).columns
y = df1.Catch_Rate.to_numpy() / 255
n_sample = X.shape[0]
n_channel = X.shape[1]
print(f'Number of samples: {n_sample}\nNumber of features: {n_channel}')
```

Number of samples: 721 Number of features: 102

2. Linear prediction

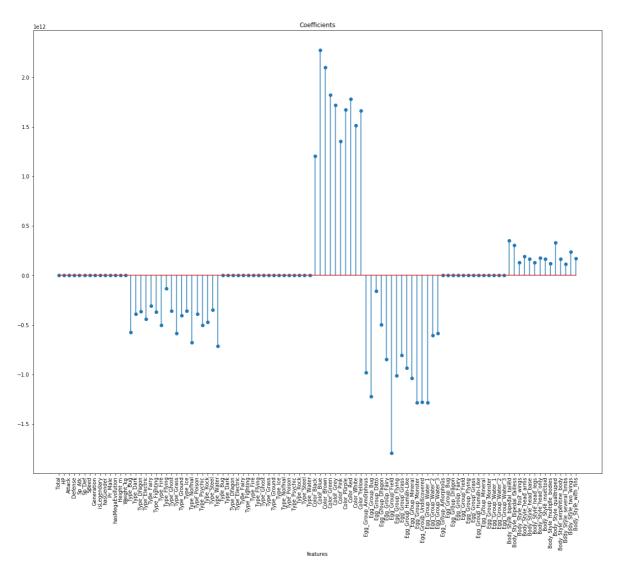
a. Basic linear regression

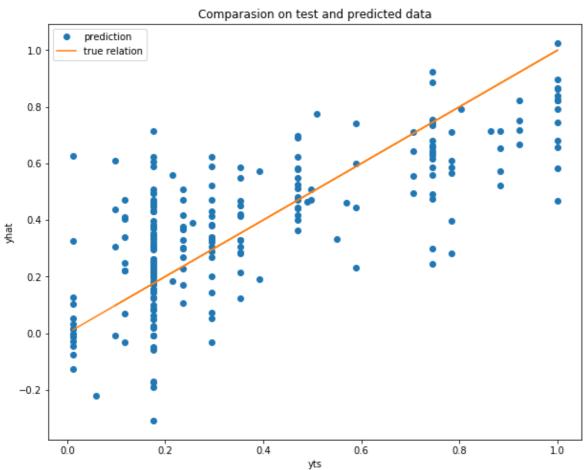
First do the normalization. Then do the linear regression.

In [28]:

```
scaling = StandardScaler()
scaling.fit(X)
X_n = scaling. transform(X)
def score (model, x, y):
    return 1 - np. mean((model.predict(x) - y)**2)
n run = 5
train_scores = []
test scores = []
coeffs = []
for i in range(n_run):
    Xtr, Xts, ytr, yts = train_test_split(X_n, y, test_size=0.33, shuffle=True)
    regr = LinearRegression()
    regr. fit (Xtr, ytr)
    yhat = regr. predict(Xts)
    train_scores.append(score(regr, Xtr, ytr))
    test_scores.append(score(regr, Xts, yts))
    coeffs. append (regr)
# print(test scores)
print(f"Train score is {np.max(train_scores)}, test score is {np.max(test_scores)}.")
best = np. argmax(test_scores)
best_coef = coeffs[best].coef_
# print(best_coef)
plt. figure (figsize=(20, 16))
plt.stem(best_coef)
plt. xlabel('features')
# plt. ylabel('$log(coef)$')
plt. title ('Coefficients')
plt.xticks(range(n_channel), labels, rotation=90)
plt.show()
plt.figure(figsize=(10, 8))
plt.plot(yts, coeffs[best].predict(Xts), 'o')
plt. plot (yts, yts)
plt. xlabel('yts')
plt.ylabel('yhat')
plt.title('Comparasion on test and predicted data')
plt.legend(['prediction', 'true relation'])
plt.show()
```

Train score is 0.974636388478952, test score is 0.9616833020611844.





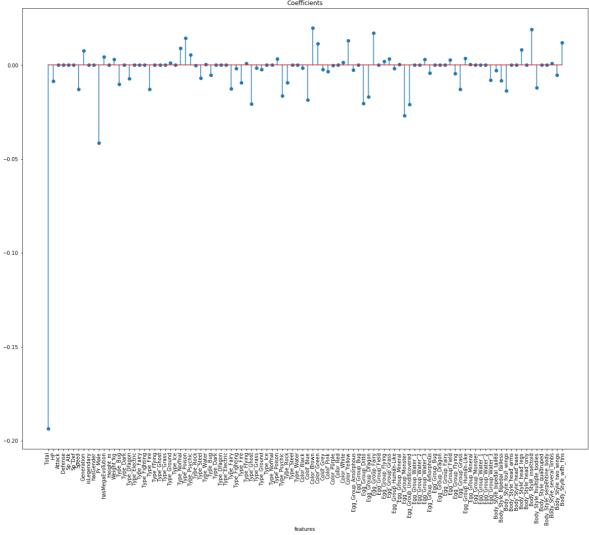
b. Linear regression with LASSO

In [29]: ▶

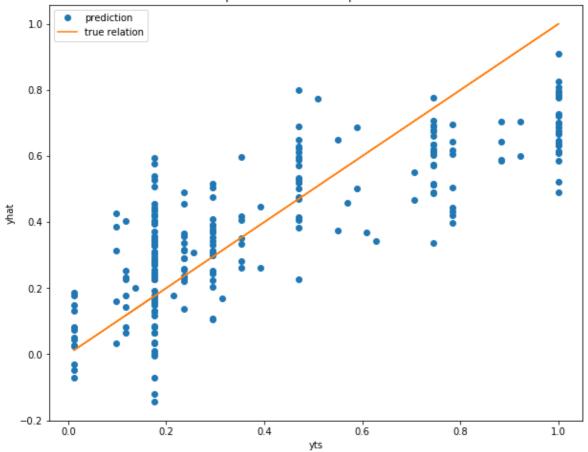
```
nalpha = 10
alphas = np. logspace (-3, 2, nalpha)
train scores = []
test_scores = []
coeffs = []
for alpha in alphas:
    for i in range(n_run):
        Xtr, Xts, ytr, yts = train_test_split(X_n, y, test_size=0.33, shuffle=True)
              print(f"calculating alpha for {alpha}")
        regr = Lasso(alpha=alpha)
        regr. fit (Xtr, ytr)
              print(f"Done {alpha}")
        yts_pred = regr. predict(Xts)
        train_scores.append(score(regr, Xtr, ytr))
        test scores.append(score(regr, Xts, yts))
        coeffs. append (regr)
print(f"Best train score is {np.max(train_scores)}, test score is {np.max(test_scores)}.")
best = np. argmax(test scores)
best_coef = coeffs[best].coef_
# print(best coef)
prominent_labels = labels[np. abs(best_coef).argsort()[-6:]][::-1]
print(f"Six most prominent features are {', '.join(prominent_labels)}")
plt.figure(figsize=(20, 16))
plt.stem(best_coef)
plt. xlabel ('features')
# plt.ylabel('$log(coef)$')
plt. title ('Coefficients')
plt.xticks(range(n_channel), labels, rotation=90)
plt.show()
plt.figure(figsize=(10, 8))
plt.plot(yts, coeffs[best].predict(Xts), 'o')
plt. plot (yts, yts)
plt. xlabel ('yts')
plt.ylabel('yhat')
plt. title ('Comparasion on test and predicted data')
plt.legend(['prediction', 'true relation'])
plt.show()
```

Best train score is 0.9732474155729648, test score is 0.9677208499056017. Six most prominent features are Total, Pr_Male, Egg_Group_Monster, Egg_Group_Undiscovered, Type_Ghost, Egg_Group_Ditto





Comparasion on test and predicted data



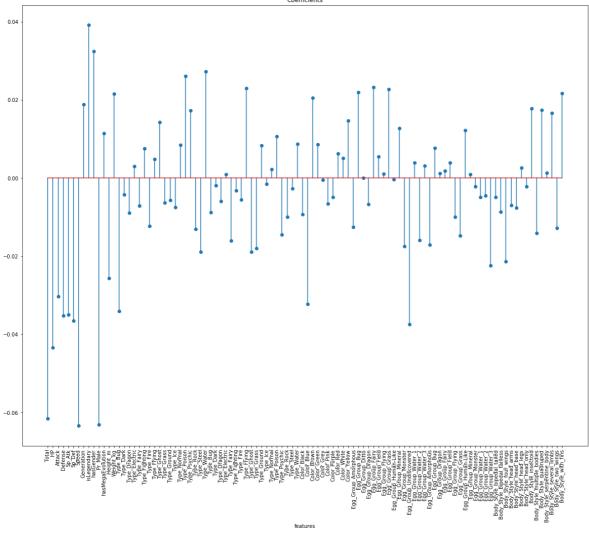
. Linear regression with Ridge	

In [30]: ▶

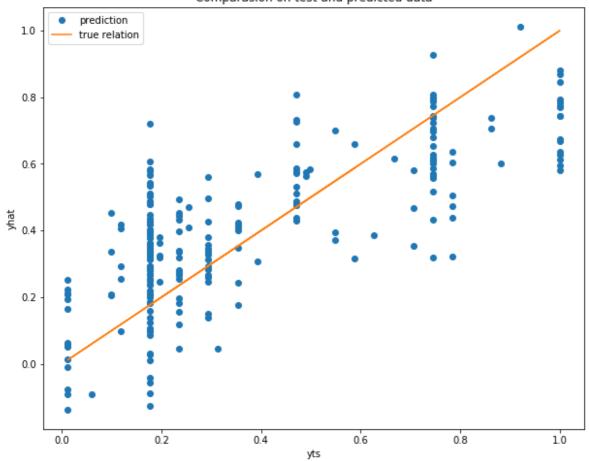
```
nalpha = 20
alphas = np. logspace (-2, 2, nalpha)
train scores = []
test_scores = []
coeffs = []
for alpha in alphas:
    for i in range(n_run):
        Xtr, Xts, ytr, yts = train test split(X n, y, test size=0.33, shuffle=True)
        regr = Ridge(alpha=alpha)
        regr. fit (Xtr, ytr)
        train_scores.append(score(regr, Xtr, ytr))
        test_scores.append(score(regr, Xts, yts))
        coeffs. append (regr)
print(f"Best train score is {np. max(train scores)}, test score is {np. max(test scores)}.")
best = np. argmax(test_scores)
best_coef = coeffs[best].coef_
# print(best_coef)
prominent_labels = labels[np.abs(best_coef).argsort()[-6:]][::-1]
print(f"Six most prominent features are {', '.join(prominent_labels)}")
plt.figure(figsize=(20, 16))
plt.stem(best_coef)
plt. xlabel('features')
# plt. ylabel('$log(coef)$')
plt.title('Coefficients')
plt. xticks (range (n channel), labels, rotation=90)
plt.show()
plt.figure(figsize=(10, 8))
plt.plot(yts, coeffs[best].predict(Xts), 'o')
plt. plot (yts, yts)
plt. xlabel ('yts')
plt.ylabel('yhat')
plt.title('Comparasion on test and predicted data')
plt.legend(['prediction', 'true relation'])
plt.show()
```

Best train score is 0.9758948312606975, test score is 0.9668559838842328. Six most prominent features are Speed, Pr_Male, Total, HP, isLegendary, Egg_Group_Un discovered





Comparasion on test and predicted data



d. Linear regression with PCA

In [0]:

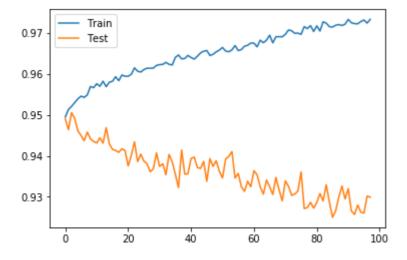
```
n_run = 10
# Number of PCs to try
ncomp_test = np.arange(2, 100)
num_nc = len(ncomp_test)
train_scores = []
test_scores = []
coeffs = []
for ncomp in ncomp_test:
    for i in range(n_run):
       Xtr, Xts, ytr, yts = train_test_split(X_n, y, test_size=0.33, shuffle=True)
        pca = PCA(n_components=ncomp, svd_solver='randomized', whiten=True)
        Xtr_transform = pca.fit_transform(Xtr)
       regr = LinearRegression()
        regr. fit(Xtr_transform, ytr)
        Xts_transform = pca.fit_transform(Xts)
        train_scores.append(score(regr, Xtr_transform, ytr))
        test_scores.append(score(regr, Xts_transform, yts))
        coeffs.append(regr.coef_)
```

In [32]:

```
# best = np. argmax(acc)
print(f"Best train score is {np. max(train_scores)}, test score is {np. max(test_scores)}.")
# print(train_scores)
# print(test_scores)
train_scores = np. array(train_scores). reshape(num_nc, -1)
test_scores = np. array(test_scores). reshape(num_nc, -1)

# keep biggest 6 and compute their mean
train_mean = np. sort(train_scores)[:, :4:-1]. mean(axis=1)
test_mean = np. sort(test_scores)[:, :4:-1]. mean(axis=1)
plt. plot(train_mean)
plt. plot(test_mean)
plt. legend(['Train', 'Test'])
plt. show()
```

Best train score is 0.9749101980907205, test score is 0.9535702528151085.



e. With neural network

In [33]:

```
class Net(nn. Module):
    def init (self, n):
        super(Net, self).__init__()
        self.net = nn. Sequential (
            nn. Linear (n, 1000),
            nn. ReLU(),
            nn. Linear (1000, 1000),
            nn. ReLU(),
            nn. Linear (1000, 1),
            nn. ReLU()
        )
    def forward(self, x):
        return self. net(x)
1r = 0.001
epochs = 100
batch size = 50
device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
dataset = utils. TensorDataset(torch. Tensor(X_n), torch. Tensor(y))
dataloader = utils.DataLoader(dataset, batch_size=50, shuffle=True)
print(f"Running on device {device}")
# Use GPU
model = Net(X_n. shape[1]). to(device)
optimizer = torch.optim.SGD(model.parameters(), 1r=1r)
criterion = nn. MSELoss()
train scores = []
losses = []
for epoch in range(1, epochs + 1):
    epoch loss = 0
    score = 0
    model = model.train()
    for index, data in enumerate (dataloader):
        x_{,} y_{,} = data
        x_{,} y_{-} = x_{.} to (device), y_{.} to (device)
        pred = model(x).view(-1)
          print(y . shape, pred. shape)
        loss = criterion(pred, y_)
          loss = torch.mean((pred - y)**2)
        epoch loss += loss.item()
        # print(f"{index*batch size:.4f} --- loss: {loss.item()/batch size:.6f}")
        optimizer.zero grad()
        loss.backward()
        optimizer.step()
    with torch.no_grad():
        X_{val} = torch. FloatTensor(X_n). to(device)
        result = model(X_val)
        pred = result.cpu().numpy()
        # score = r2 score(y, pred)
```

```
score = 1 - np.mean((y - pred[0, :])**2)
    train_scores.append(score)
    losses.append(epoch loss / len(dataset))
      print(f'Epoch {epoch} finished! Loss: {epoch_loss / len(dataset):.4f} Score: {score:.6f}')
    torch. save(model.state_dict(), 'saved.model')
with torch.no_grad():
      X val = torch.FloatTensor(X n).to(device)
      result = model(X_val)
      pred = result.cpu().numpy()
      plt. figure (figsize=(10, 8))
      plt.plot(y, pred, 'o')
      plt. plot (y, y)
      plt.xlabel('y')
      plt. ylabel('yhat')
      plt.title('Comparasion on real and predicted data')
      plt.legend(['prediction', 'true relation'])
      plt.show()
plt. figure (figsize=(10, 8))
plt.plot(train_scores,'x-')
# plt. plot (losses)
plt. xlabel ('epoch')
plt. ylabel('score')
plt. title('Score')
# plt.legend(['Score', 'Loss'])
plt.show()
```

Running on device cuda:0



