Congratulations! You have been hired by Fairfield Advisors LLC. to create a Artificial Neural Network to determine the price of the ^VIX volatility index. You will be provided the Data and features that will be trained to predict the value of the ^VIX index. Along with predicting the value of VIX you will need to create another mode that will classify ^VIX as dummy variables (1,0) , with 1 being a positive in the Daily Adj Close, and 0 beinng a daily loss in the ADJ CLOSE. Capture the error in the model and report if its is significant relative to predicitions of VIX.

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

In [2]:
```
import seaborn as sns
from plotly.offline import plot, iplot, download_plotlyjs, init_notebook
_mode
import cufflinks as cf
```

In [3]:
```
cf.go_offline()
init_notebook_mode(connected=False)
```

In [4]:
```
vix_data = pd.read_csv("resources/vix_data_cleaned")
```

In [5]:
```
vix_data["dates"] = pd.to_datetime(vix_data["dates"])
```

In [6]:
```
vix_data.set_index("dates", inplace=True)
```

In [7]:
```
vix_data.replace([np.inf, -np.inf], np.nan)
```

Out[7]:

dates	UVXY	SPY	VXXBEN	VIX	UX1	UX2	UX3	UX4	Day of Week	Days to Roll	...	
2006-10-23	8.377069e+09	137.47	1.9100	11.08	11.950	13.160	14.080	14.600	2	17	...	
2006-10-24	8.377069e+09	137.88	2.0250	10.78	11.780	12.830	14.030	14.470	3	16	...	-0
2006-10-25	7.968986e+09	138.35	1.7600	10.66	11.490	12.520	13.790	14.520	4	15	...	-0
2006-10-26	7.618653e+09	138.78	1.5150	10.56	11.250	12.210	13.460	14.180	5	14	...	-0
2006-10-27	7.695087e+09	137.91	1.2400	10.80	11.310	12.260	13.460	14.240	6	13	...	0
...	...	...	...	...	...	...	...	...	...	...	...	
2019-09-10	2.730000e+01	298.13	2.2625	15.20	16.225	17.675	18.025	17.875	2	5	...	-0
2019-09-11	2.661000e+01	300.25	2.4725	14.61	15.725	17.325	17.825	17.725	3	4	...	-0
2019-09-12	2.565000e+01	301.29	2.1575	14.22	14.975	17.025	17.625	17.575	4	3	...	-0
2019-09-13	2.511000e+01	301.09	2.3025	13.74	14.475	16.875	17.575	17.625	5	2	...	-0
2019-09-16	2.565000e+01	300.16	1.2575	14.67	14.625	17.275	17.925	17.925	1	1	...	0

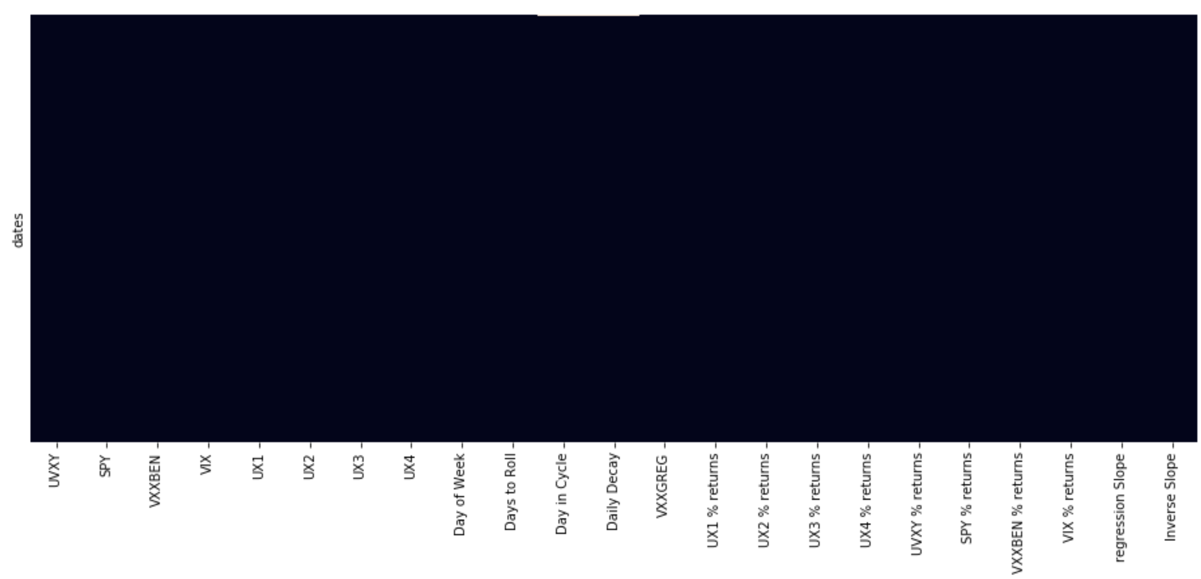
3246 rows × 23 columns

In [8]:
```python
vix_data.isnull().sum()
```

Out[8]:
```
UVXY                 0
SPY                  0
VXXBEN               0
VIX                  0
UX1                  0
UX2                  0
UX3                  0
UX4                  0
Day of Week          0
Days to Roll         0
Day in Cycle        17
Daily Decay         17
VXXGREG              0
UX1 % returns        1
UX2 % returns        1
UX3 % returns        1
UX4 % returns        1
UVXY % returns       1
SPY % returns        1
VXXBEN % returns     1
VIX % returns        1
regression Slope     1
Inverse Slope        2
dtype: int64
```

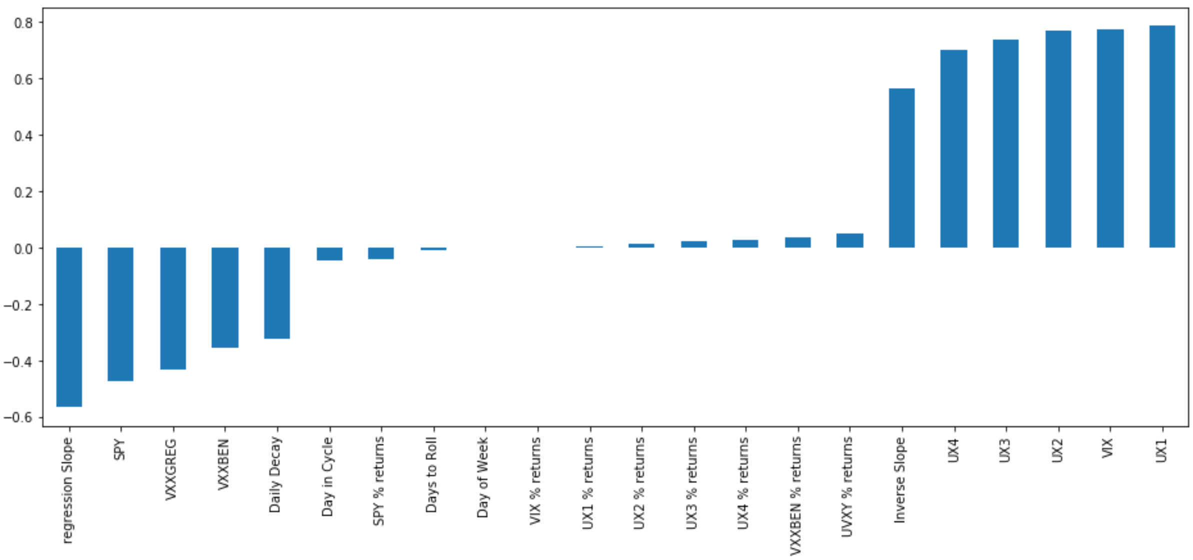
In [9]:
```python
plt.figure(figsize=(16,6))
sns.heatmap(vix_data.isnull(), yticklabels=False, cbar=False )
```

Out[9]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x10b832fd0>
```



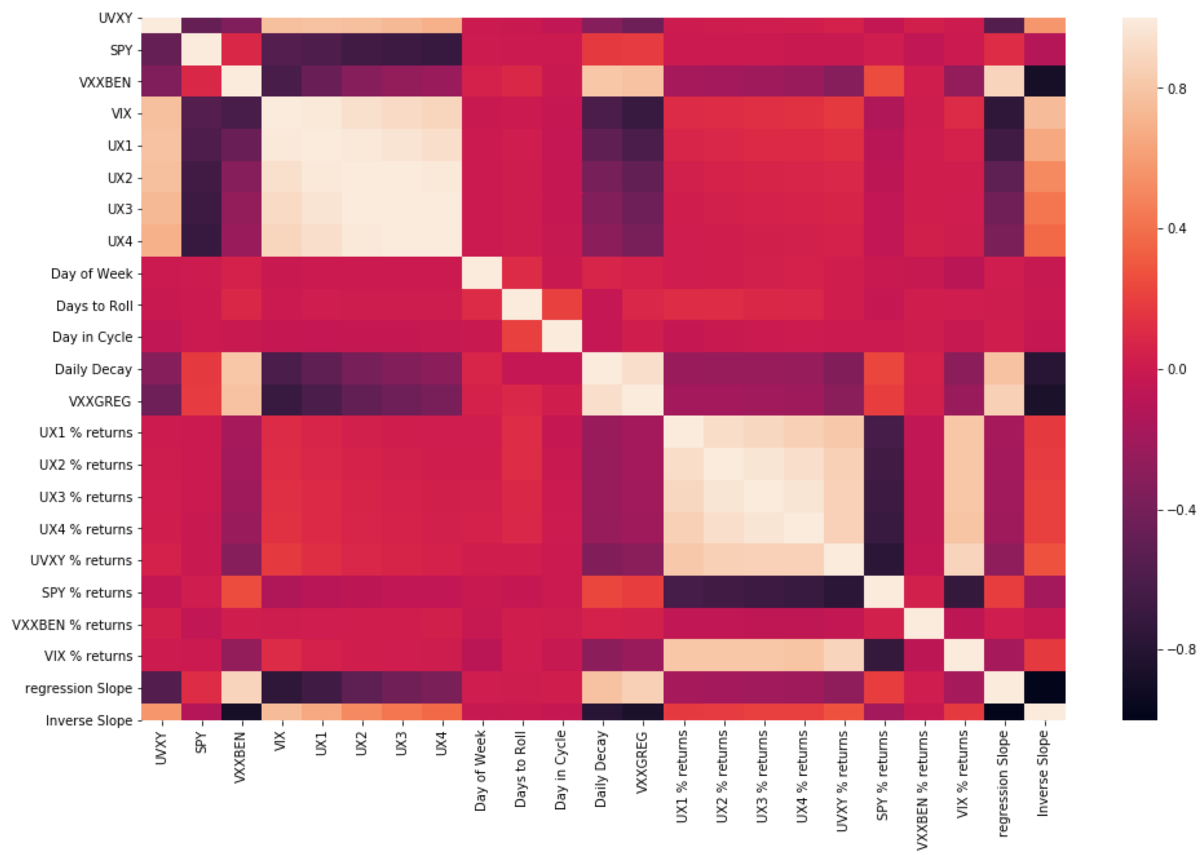
In [10]:
```
vix_data.corr()["UVXY"][1:].sort_values().plot(kind = "bar", figsize = (
16,6))
```

Out[10]: <matplotlib.axes._subplots.AxesSubplot at 0x11b4f7650>



In [11]:
```
plt.figure(figsize=(16,10))
sns.heatmap(vix_data.corr())
```

Out[11]: <matplotlib.axes._subplots.AxesSubplot at 0x1c2435e390>



we will use a dummy approach to determin if VIX will be a loss or a gain daily. Meaning we will represent a gain as 1 and a loss as 0. we will then apply ML and ANN to make predictions on vix

In [12]:
```
def check_losses(vix_column):
    if vix_column < 0:
        return 0
    else:
        return 1
```

In [13]:
```
vix_data["target"] = vix_data["VIX % returns"].apply(check_losses)
```

In [14]:
```
vix_data["target"]
```

Out[14]:
```
dates
2006-10-23    1
2006-10-24    0
2006-10-25    0
2006-10-26    0
2006-10-27    1
             ..
2019-09-10    0
2019-09-11    0
2019-09-12    0
2019-09-13    0
2019-09-16    1
Name: target, Length: 3246, dtype: int64
```

In [15]:
```
vix_data.columns
```

Out[15]:
```
Index(['UVXY', 'SPY', 'VXXBEN', 'VIX', 'UX1', 'UX2', 'UX3', 'UX4',
       'Day of Week', 'Days to Roll', 'Day in Cycle', 'Daily Decay', 'V
XXGREG',
       'UX1 % returns', 'UX2 % returns', 'UX3 % returns', 'UX4 % return
s',
       'UVXY % returns', 'SPY % returns', 'VXXBEN % returns', 'VIX % re
turns',
       'regression Slope', 'Inverse Slope', 'target'],
      dtype='object')
```

Prepping our data

- Target will be a sigmoid classificaion of vix % return..Our model will predict if VIX will have a negative return or a gain. We will first have to remove the VIX % return column because it is a perfect predictor for our target and will infere with our model predicitons

In [21]:
```
model_data = vix_data.replace([np.inf, -np.inf], np.nan).dropna()
```

In [23]:
```
model_data.drop("VIX % returns", inplace=True, axis=1)
```

Training The Data

In [35]:
```
X = model_data.drop("target", axis=1).values
y = model_data["target"].values
```

In [36]:
```
from sklearn.model_selection import train_test_split
```

In [37]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30
, random_state=101)
```

Scaling our Data

In [38]:
```
from sklearn.preprocessing import MinMaxScaler
```

In [39]:
```
scalar = MinMaxScaler()
```

In [40]:
```
X_train = scalar.fit_transform(X_train)
```

In [41]:
```
X_test = scalar.transform(X_test)
```

Creating our model

In [42]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.callbacks import EarlyStopping, TensorBoard
```

In [43]:
```
X_train.shape
```

Out[43]:
```
(2259, 22)
```

In [44]:
```
model = Sequential()
model.add(Dense(units = 22, activation = "relu"))
model.add(Dense(units = 11, activation = "relu"))
model.add(Dense(units = 6, activation = "relu"))
model.add(Dense(units = 1, activation = "sigmoid"))
model.compile(optimizer = "adam", loss = "binary_crossentropy")
```

In [45]:
```
model.fit(X_train,y_train, validation_data=(X_test,y_test), epochs=200)
```

```
Train on 2259 samples, validate on 969 samples
Epoch 1/200
2259/2259 [==============================] - 2s 926us/sample - loss: 0.
6859 - val_loss: 0.6731
Epoch 2/200
2259/2259 [==============================] - 0s 176us/sample - loss: 0.
6601 - val_loss: 0.6433
Epoch 3/200
2259/2259 [==============================] - 0s 167us/sample - loss: 0.
6232 - val_loss: 0.5938
Epoch 4/200
2259/2259 [==============================] - 0s 167us/sample - loss: 0.
5693 - val_loss: 0.5398
Epoch 5/200
2259/2259 [==============================] - 0s 173us/sample - loss: 0.
5140 - val_loss: 0.4783
Epoch 6/200
2259/2259 [==============================] - 0s 169us/sample - loss: 0.
4676 - val_loss: 0.4779
Epoch 7/200
2259/2259 [==============================] - 0s 172us/sample - loss: 0.
4291 - val_loss: 0.4028
Epoch 8/200
2259/2259 [==============================] - 0s 181us/sample - loss: 0.
4104 - val_loss: 0.3835
Epoch 9/200
2259/2259 [==============================] - 0s 172us/sample - loss: 0.
3976 - val_loss: 0.3783
Epoch 10/200
2259/2259 [==============================] - 0s 192us/sample - loss: 0.
3717 - val_loss: 0.3569
Epoch 11/200
2259/2259 [==============================] - 0s 169us/sample - loss: 0.
3663 - val_loss: 0.3463
Epoch 12/200
2259/2259 [==============================] - 0s 174us/sample - loss: 0.
3560 - val_loss: 0.3430
Epoch 13/200
2259/2259 [==============================] - 0s 170us/sample - loss: 0.
3495 - val_loss: 0.3377
Epoch 14/200
2259/2259 [==============================] - 0s 182us/sample - loss: 0.
3507 - val_loss: 0.3366
Epoch 15/200
2259/2259 [==============================] - 0s 174us/sample - loss: 0.
3426 - val_loss: 0.3227
Epoch 16/200
2259/2259 [==============================] - 0s 178us/sample - loss: 0.
3384 - val_loss: 0.3192
Epoch 17/200
2259/2259 [==============================] - 0s 177us/sample - loss: 0.
3350 - val_loss: 0.3168
Epoch 18/200
2259/2259 [==============================] - 0s 175us/sample - loss: 0.
3265 - val_loss: 0.3412
Epoch 19/200
2259/2259 [==============================] - 0s 182us/sample - loss: 0.
```

```
3330 - val_loss: 0.3118
Epoch 20/200
2259/2259 [==============================] - 0s 175us/sample - loss: 0.
3271 - val_loss: 0.3137
Epoch 21/200
2259/2259 [==============================] - 0s 172us/sample - loss: 0.
3260 - val_loss: 0.3206
Epoch 22/200
2259/2259 [==============================] - 0s 174us/sample - loss: 0.
3205 - val_loss: 0.3134
Epoch 23/200
2259/2259 [==============================] - 0s 175us/sample - loss: 0.
3189 - val_loss: 0.3142
Epoch 24/200
2259/2259 [==============================] - 0s 176us/sample - loss: 0.
3161 - val_loss: 0.3134
Epoch 25/200
2259/2259 [==============================] - 0s 188us/sample - loss: 0.
3185 - val_loss: 0.3095
Epoch 26/200
2259/2259 [==============================] - 0s 175us/sample - loss: 0.
3107 - val_loss: 0.3078
Epoch 27/200
2259/2259 [==============================] - 0s 171us/sample - loss: 0.
3197 - val_loss: 0.3093
Epoch 28/200
2259/2259 [==============================] - 0s 171us/sample - loss: 0.
3214 - val_loss: 0.3027
Epoch 29/200
2259/2259 [==============================] - 0s 178us/sample - loss: 0.
3156 - val_loss: 0.3023
Epoch 30/200
2259/2259 [==============================] - 0s 175us/sample - loss: 0.
3101 - val_loss: 0.3016
Epoch 31/200
2259/2259 [==============================] - 0s 171us/sample - loss: 0.
3115 - val_loss: 0.3028
Epoch 32/200
2259/2259 [==============================] - 0s 170us/sample - loss: 0.
3045 - val_loss: 0.3011
Epoch 33/200
2259/2259 [==============================] - 0s 167us/sample - loss: 0.
3048 - val_loss: 0.3013
Epoch 34/200
2259/2259 [==============================] - 0s 173us/sample - loss: 0.
3160 - val_loss: 0.3130
Epoch 35/200
2259/2259 [==============================] - 0s 187us/sample - loss: 0.
3082 - val_loss: 0.3010
Epoch 36/200
2259/2259 [==============================] - 0s 206us/sample - loss: 0.
3003 - val_loss: 0.3040
Epoch 37/200
2259/2259 [==============================] - 0s 196us/sample - loss: 0.
3016 - val_loss: 0.3040
Epoch 38/200
2259/2259 [==============================] - 0s 175us/sample - loss: 0.
```

```
2982 - val_loss: 0.3094
Epoch 39/200
2259/2259 [==============================] - 0s 185us/sample - loss: 0.
3026 - val_loss: 0.3241
Epoch 40/200
2259/2259 [==============================] - 0s 175us/sample - loss: 0.
3040 - val_loss: 0.3036
Epoch 41/200
2259/2259 [==============================] - 0s 177us/sample - loss: 0.
2945 - val_loss: 0.2995
Epoch 42/200
2259/2259 [==============================] - 0s 172us/sample - loss: 0.
2997 - val_loss: 0.3237
Epoch 43/200
2259/2259 [==============================] - 0s 169us/sample - loss: 0.
3020 - val_loss: 0.2979
Epoch 44/200
2259/2259 [==============================] - 0s 169us/sample - loss: 0.
2944 - val_loss: 0.3024
Epoch 45/200
2259/2259 [==============================] - 0s 171us/sample - loss: 0.
2919 - val_loss: 0.3038
Epoch 46/200
2259/2259 [==============================] - 0s 169us/sample - loss: 0.
2968 - val_loss: 0.2983
Epoch 47/200
2259/2259 [==============================] - 0s 167us/sample - loss: 0.
2892 - val_loss: 0.3029
Epoch 48/200
2259/2259 [==============================] - 0s 170us/sample - loss: 0.
2943 - val_loss: 0.2990
Epoch 49/200
2259/2259 [==============================] - 0s 171us/sample - loss: 0.
3009 - val_loss: 0.3163
Epoch 50/200
2259/2259 [==============================] - 0s 168us/sample - loss: 0.
2941 - val_loss: 0.2995
Epoch 51/200
2259/2259 [==============================] - 0s 171us/sample - loss: 0.
2892 - val_loss: 0.3007
Epoch 52/200
2259/2259 [==============================] - 0s 170us/sample - loss: 0.
2934 - val_loss: 0.2980
Epoch 53/200
2259/2259 [==============================] - 0s 171us/sample - loss: 0.
2911 - val_loss: 0.3081
Epoch 54/200
2259/2259 [==============================] - 0s 171us/sample - loss: 0.
2864 - val_loss: 0.2965
Epoch 55/200
2259/2259 [==============================] - 0s 171us/sample - loss: 0.
2951 - val_loss: 0.3225
Epoch 56/200
2259/2259 [==============================] - 0s 172us/sample - loss: 0.
2985 - val_loss: 0.3004
Epoch 57/200
2259/2259 [==============================] - 0s 168us/sample - loss: 0.
```

```
2891 - val_loss: 0.2991
Epoch 58/200
2259/2259 [==============================] - 0s 169us/sample - loss: 0.
2874 - val_loss: 0.2973
Epoch 59/200
2259/2259 [==============================] - 0s 172us/sample - loss: 0.
2875 - val_loss: 0.3053
Epoch 60/200
2259/2259 [==============================] - 0s 170us/sample - loss: 0.
2915 - val_loss: 0.3034
Epoch 61/200
2259/2259 [==============================] - 0s 170us/sample - loss: 0.
2881 - val_loss: 0.3008
Epoch 62/200
2259/2259 [==============================] - 0s 168us/sample - loss: 0.
2875 - val_loss: 0.3021
Epoch 63/200
2259/2259 [==============================] - 0s 170us/sample - loss: 0.
2859 - val_loss: 0.3026
Epoch 64/200
2259/2259 [==============================] - 0s 170us/sample - loss: 0.
2860 - val_loss: 0.2977
Epoch 65/200
2259/2259 [==============================] - 0s 168us/sample - loss: 0.
2872 - val_loss: 0.3009
Epoch 66/200
2259/2259 [==============================] - 0s 170us/sample - loss: 0.
2861 - val_loss: 0.3018
Epoch 67/200
2259/2259 [==============================] - 0s 169us/sample - loss: 0.
2855 - val_loss: 0.2965
Epoch 68/200
2259/2259 [==============================] - 0s 168us/sample - loss: 0.
2870 - val_loss: 0.2937
Epoch 69/200
2259/2259 [==============================] - 0s 168us/sample - loss: 0.
2824 - val_loss: 0.3021
Epoch 70/200
2259/2259 [==============================] - 0s 169us/sample - loss: 0.
2877 - val_loss: 0.2954
Epoch 71/200
2259/2259 [==============================] - 0s 172us/sample - loss: 0.
2819 - val_loss: 0.2955
Epoch 72/200
2259/2259 [==============================] - 0s 170us/sample - loss: 0.
2813 - val_loss: 0.2927
Epoch 73/200
2259/2259 [==============================] - 0s 168us/sample - loss: 0.
2791 - val_loss: 0.2959
Epoch 74/200
2259/2259 [==============================] - 0s 170us/sample - loss: 0.
2852 - val_loss: 0.2944
Epoch 75/200
2259/2259 [==============================] - 0s 168us/sample - loss: 0.
2928 - val_loss: 0.2944
Epoch 76/200
2259/2259 [==============================] - 0s 175us/sample - loss: 0.
```

```
2802 - val_loss: 0.2962
Epoch 77/200
2259/2259 [==============================] - 0s 173us/sample - loss: 0.
2805 - val_loss: 0.3095
Epoch 78/200
2259/2259 [==============================] - 0s 166us/sample - loss: 0.
2818 - val_loss: 0.2951
Epoch 79/200
2259/2259 [==============================] - 0s 167us/sample - loss: 0.
2865 - val_loss: 0.2997
Epoch 80/200
2259/2259 [==============================] - 0s 162us/sample - loss: 0.
2786 - val_loss: 0.2941
Epoch 81/200
2259/2259 [==============================] - 0s 165us/sample - loss: 0.
2808 - val_loss: 0.2960
Epoch 82/200
2259/2259 [==============================] - 0s 162us/sample - loss: 0.
2833 - val_loss: 0.3441
Epoch 83/200
2259/2259 [==============================] - 0s 165us/sample - loss: 0.
2973 - val_loss: 0.3033
Epoch 84/200
2259/2259 [==============================] - 0s 166us/sample - loss: 0.
2844 - val_loss: 0.2915
Epoch 85/200
2259/2259 [==============================] - 0s 167us/sample - loss: 0.
2828 - val_loss: 0.2939
Epoch 86/200
2259/2259 [==============================] - 0s 162us/sample - loss: 0.
2773 - val_loss: 0.2967
Epoch 87/200
2259/2259 [==============================] - 0s 161us/sample - loss: 0.
2798 - val_loss: 0.2969
Epoch 88/200
2259/2259 [==============================] - 0s 165us/sample - loss: 0.
2860 - val_loss: 0.3041
Epoch 89/200
2259/2259 [==============================] - 0s 168us/sample - loss: 0.
2764 - val_loss: 0.2918
Epoch 90/200
2259/2259 [==============================] - 0s 162us/sample - loss: 0.
2780 - val_loss: 0.2973
Epoch 91/200
2259/2259 [==============================] - 0s 172us/sample - loss: 0.
2778 - val_loss: 0.2901
Epoch 92/200
2259/2259 [==============================] - 0s 165us/sample - loss: 0.
2830 - val_loss: 0.2908
Epoch 93/200
2259/2259 [==============================] - 0s 165us/sample - loss: 0.
2798 - val_loss: 0.3070
Epoch 94/200
2259/2259 [==============================] - 0s 165us/sample - loss: 0.
2825 - val_loss: 0.2929
Epoch 95/200
2259/2259 [==============================] - 0s 166us/sample - loss: 0.
```

```
2763 - val_loss: 0.2920
Epoch 96/200
2259/2259 [==============================] - 0s 164us/sample - loss: 0.
2745 - val_loss: 0.2921
Epoch 97/200
2259/2259 [==============================] - 0s 164us/sample - loss: 0.
2799 - val_loss: 0.2957
Epoch 98/200
2259/2259 [==============================] - 0s 162us/sample - loss: 0.
2812 - val_loss: 0.2984
Epoch 99/200
2259/2259 [==============================] - 0s 165us/sample - loss: 0.
2777 - val_loss: 0.2945
Epoch 100/200
2259/2259 [==============================] - 0s 171us/sample - loss: 0.
2817 - val_loss: 0.3102
Epoch 101/200
2259/2259 [==============================] - 0s 165us/sample - loss: 0.
2755 - val_loss: 0.2909
Epoch 102/200
2259/2259 [==============================] - 0s 163us/sample - loss: 0.
2855 - val_loss: 0.3010
Epoch 103/200
2259/2259 [==============================] - 0s 172us/sample - loss: 0.
2834 - val_loss: 0.2942
Epoch 104/200
2259/2259 [==============================] - 0s 176us/sample - loss: 0.
2760 - val_loss: 0.3113
Epoch 105/200
2259/2259 [==============================] - 0s 163us/sample - loss: 0.
2807 - val_loss: 0.2964
Epoch 106/200
2259/2259 [==============================] - 0s 166us/sample - loss: 0.
2767 - val_loss: 0.3104
Epoch 107/200
2259/2259 [==============================] - 0s 162us/sample - loss: 0.
2794 - val_loss: 0.3008
Epoch 108/200
2259/2259 [==============================] - 0s 166us/sample - loss: 0.
2885 - val_loss: 0.3050
Epoch 109/200
2259/2259 [==============================] - 0s 165us/sample - loss: 0.
2803 - val_loss: 0.2913
Epoch 110/200
2259/2259 [==============================] - 0s 169us/sample - loss: 0.
2732 - val_loss: 0.2951
Epoch 111/200
2259/2259 [==============================] - 0s 162us/sample - loss: 0.
2725 - val_loss: 0.3478
Epoch 112/200
2259/2259 [==============================] - 0s 165us/sample - loss: 0.
2977 - val_loss: 0.2898
Epoch 113/200
2259/2259 [==============================] - 0s 166us/sample - loss: 0.
2835 - val_loss: 0.2911
Epoch 114/200
2259/2259 [==============================] - 0s 170us/sample - loss: 0.
```

```
2764 - val_loss: 0.2986
Epoch 115/200
2259/2259 [==============================] - 0s 166us/sample - loss: 0.
2832 - val_loss: 0.2878
Epoch 116/200
2259/2259 [==============================] - 0s 166us/sample - loss: 0.
2775 - val_loss: 0.2923
Epoch 117/200
2259/2259 [==============================] - 0s 168us/sample - loss: 0.
2736 - val_loss: 0.2926
Epoch 118/200
2259/2259 [==============================] - 0s 167us/sample - loss: 0.
2708 - val_loss: 0.2889
Epoch 119/200
2259/2259 [==============================] - 0s 165us/sample - loss: 0.
2760 - val_loss: 0.2876
Epoch 120/200
2259/2259 [==============================] - 0s 165us/sample - loss: 0.
2767 - val_loss: 0.2898
Epoch 121/200
2259/2259 [==============================] - 0s 169us/sample - loss: 0.
2723 - val_loss: 0.2876
Epoch 122/200
2259/2259 [==============================] - 0s 163us/sample - loss: 0.
2890 - val_loss: 0.2919
Epoch 123/200
2259/2259 [==============================] - 0s 168us/sample - loss: 0.
2822 - val_loss: 0.3433
Epoch 124/200
2259/2259 [==============================] - 0s 175us/sample - loss: 0.
2770 - val_loss: 0.2997
Epoch 125/200
2259/2259 [==============================] - 0s 166us/sample - loss: 0.
2796 - val_loss: 0.2893
Epoch 126/200
2259/2259 [==============================] - 0s 167us/sample - loss: 0.
2783 - val_loss: 0.2999
Epoch 127/200
2259/2259 [==============================] - 0s 163us/sample - loss: 0.
2724 - val_loss: 0.3583
Epoch 128/200
2259/2259 [==============================] - 0s 162us/sample - loss: 0.
2744 - val_loss: 0.2909
Epoch 129/200
2259/2259 [==============================] - 0s 165us/sample - loss: 0.
2721 - val_loss: 0.2968
Epoch 130/200
2259/2259 [==============================] - 0s 163us/sample - loss: 0.
2766 - val_loss: 0.2885
Epoch 131/200
2259/2259 [==============================] - 0s 169us/sample - loss: 0.
2762 - val_loss: 0.3065
Epoch 132/200
2259/2259 [==============================] - 0s 170us/sample - loss: 0.
2842 - val_loss: 0.3029
Epoch 133/200
2259/2259 [==============================] - 0s 167us/sample - loss: 0.
```

```
2779 - val_loss: 0.2966
Epoch 134/200
2259/2259 [==============================] - 0s 163us/sample - loss: 0.
2765 - val_loss: 0.3020
Epoch 135/200
2259/2259 [==============================] - 0s 166us/sample - loss: 0.
2777 - val_loss: 0.2875
Epoch 136/200
2259/2259 [==============================] - 0s 167us/sample - loss: 0.
2791 - val_loss: 0.2862
Epoch 137/200
2259/2259 [==============================] - 0s 164us/sample - loss: 0.
2730 - val_loss: 0.2876
Epoch 138/200
2259/2259 [==============================] - 0s 167us/sample - loss: 0.
2827 - val_loss: 0.2887
Epoch 139/200
2259/2259 [==============================] - 0s 170us/sample - loss: 0.
2733 - val_loss: 0.3108
Epoch 140/200
2259/2259 [==============================] - 0s 171us/sample - loss: 0.
2752 - val_loss: 0.2872
Epoch 141/200
2259/2259 [==============================] - 0s 165us/sample - loss: 0.
2838 - val_loss: 0.2848
Epoch 142/200
2259/2259 [==============================] - 0s 165us/sample - loss: 0.
2749 - val_loss: 0.2915
Epoch 143/200
2259/2259 [==============================] - 0s 167us/sample - loss: 0.
2763 - val_loss: 0.2906
Epoch 144/200
2259/2259 [==============================] - 0s 164us/sample - loss: 0.
2726 - val_loss: 0.2904
Epoch 145/200
2259/2259 [==============================] - 0s 165us/sample - loss: 0.
2760 - val_loss: 0.2882
Epoch 146/200
2259/2259 [==============================] - 0s 169us/sample - loss: 0.
2714 - val_loss: 0.2951
Epoch 147/200
2259/2259 [==============================] - 0s 168us/sample - loss: 0.
2779 - val_loss: 0.3078
Epoch 148/200
2259/2259 [==============================] - 0s 162us/sample - loss: 0.
2739 - val_loss: 0.2857
Epoch 149/200
2259/2259 [==============================] - 0s 167us/sample - loss: 0.
2700 - val_loss: 0.3171
Epoch 150/200
2259/2259 [==============================] - 0s 164us/sample - loss: 0.
2831 - val_loss: 0.2875
Epoch 151/200
2259/2259 [==============================] - 0s 167us/sample - loss: 0.
2697 - val_loss: 0.2889
Epoch 152/200
2259/2259 [==============================] - 0s 167us/sample - loss: 0.
```

```
2690 - val_loss: 0.3017
Epoch 153/200
2259/2259 [==============================] - 0s 171us/sample - loss: 0.
2737 - val_loss: 0.2855
Epoch 154/200
2259/2259 [==============================] - 0s 167us/sample - loss: 0.
2707 - val_loss: 0.2889
Epoch 155/200
2259/2259 [==============================] - 0s 166us/sample - loss: 0.
2691 - val_loss: 0.2967
Epoch 156/200
2259/2259 [==============================] - 0s 168us/sample - loss: 0.
2737 - val_loss: 0.2881
Epoch 157/200
2259/2259 [==============================] - 0s 172us/sample - loss: 0.
2757 - val_loss: 0.2862
Epoch 158/200
2259/2259 [==============================] - 0s 179us/sample - loss: 0.
2687 - val_loss: 0.3367
Epoch 159/200
2259/2259 [==============================] - 0s 166us/sample - loss: 0.
2804 - val_loss: 0.2978
Epoch 160/200
2259/2259 [==============================] - 0s 162us/sample - loss: 0.
2708 - val_loss: 0.2877
Epoch 161/200
2259/2259 [==============================] - 0s 165us/sample - loss: 0.
2700 - val_loss: 0.2945
Epoch 162/200
2259/2259 [==============================] - 0s 165us/sample - loss: 0.
2764 - val_loss: 0.3022
Epoch 163/200
2259/2259 [==============================] - 0s 166us/sample - loss: 0.
2760 - val_loss: 0.3066
Epoch 164/200
2259/2259 [==============================] - 0s 164us/sample - loss: 0.
2695 - val_loss: 0.3063
Epoch 165/200
2259/2259 [==============================] - 0s 165us/sample - loss: 0.
2718 - val_loss: 0.2932
Epoch 166/200
2259/2259 [==============================] - 0s 169us/sample - loss: 0.
2674 - val_loss: 0.2893
Epoch 167/200
2259/2259 [==============================] - 0s 163us/sample - loss: 0.
2666 - val_loss: 0.2957
Epoch 168/200
2259/2259 [==============================] - 0s 175us/sample - loss: 0.
2675 - val_loss: 0.3606
Epoch 169/200
2259/2259 [==============================] - 0s 170us/sample - loss: 0.
2767 - val_loss: 0.3038
Epoch 170/200
2259/2259 [==============================] - 0s 187us/sample - loss: 0.
2707 - val_loss: 0.2991
Epoch 171/200
2259/2259 [==============================] - 0s 190us/sample - loss: 0.
```

```
2813 - val_loss: 0.2968
Epoch 172/200
2259/2259 [==============================] - 0s 194us/sample - loss: 0.
2714 - val_loss: 0.3160
Epoch 173/200
2259/2259 [==============================] - 0s 181us/sample - loss: 0.
2699 - val_loss: 0.2869
Epoch 174/200
2259/2259 [==============================] - 0s 174us/sample - loss: 0.
2720 - val_loss: 0.2941
Epoch 175/200
2259/2259 [==============================] - 0s 176us/sample - loss: 0.
2675 - val_loss: 0.3207
Epoch 176/200
2259/2259 [==============================] - 0s 177us/sample - loss: 0.
2748 - val_loss: 0.2864
Epoch 177/200
2259/2259 [==============================] - 0s 173us/sample - loss: 0.
2675 - val_loss: 0.2849
Epoch 178/200
2259/2259 [==============================] - 0s 170us/sample - loss: 0.
2752 - val_loss: 0.2918
Epoch 179/200
2259/2259 [==============================] - 0s 176us/sample - loss: 0.
2655 - val_loss: 0.2885
Epoch 180/200
2259/2259 [==============================] - 0s 175us/sample - loss: 0.
2648 - val_loss: 0.2902
Epoch 181/200
2259/2259 [==============================] - 0s 179us/sample - loss: 0.
2630 - val_loss: 0.2925
Epoch 182/200
2259/2259 [==============================] - 0s 174us/sample - loss: 0.
2644 - val_loss: 0.2893
Epoch 183/200
2259/2259 [==============================] - 0s 176us/sample - loss: 0.
2676 - val_loss: 0.2879
Epoch 184/200
2259/2259 [==============================] - 0s 180us/sample - loss: 0.
2692 - val_loss: 0.3151
Epoch 185/200
2259/2259 [==============================] - 0s 169us/sample - loss: 0.
2765 - val_loss: 0.3094
Epoch 186/200
2259/2259 [==============================] - 0s 168us/sample - loss: 0.
2629 - val_loss: 0.3094
Epoch 187/200
2259/2259 [==============================] - 0s 171us/sample - loss: 0.
2670 - val_loss: 0.2877
Epoch 188/200
2259/2259 [==============================] - 0s 169us/sample - loss: 0.
2649 - val_loss: 0.3030
Epoch 189/200
2259/2259 [==============================] - 0s 168us/sample - loss: 0.
2719 - val_loss: 0.2895
Epoch 190/200
2259/2259 [==============================] - 0s 173us/sample - loss: 0.
```

```
2643 - val_loss: 0.2911
Epoch 191/200
2259/2259 [==============================] - 0s 178us/sample - loss: 0.
2668 - val_loss: 0.2884
Epoch 192/200
2259/2259 [==============================] - 0s 174us/sample - loss: 0.
2640 - val_loss: 0.2925
Epoch 193/200
2259/2259 [==============================] - 0s 178us/sample - loss: 0.
2610 - val_loss: 0.2888
Epoch 194/200
2259/2259 [==============================] - 0s 175us/sample - loss: 0.
2679 - val_loss: 0.2993
Epoch 195/200
2259/2259 [==============================] - 0s 172us/sample - loss: 0.
2638 - val_loss: 0.2921
Epoch 196/200
2259/2259 [==============================] - 0s 174us/sample - loss: 0.
2726 - val_loss: 0.3016
Epoch 197/200
2259/2259 [==============================] - 0s 177us/sample - loss: 0.
2611 - val_loss: 0.2879
Epoch 198/200
2259/2259 [==============================] - 0s 183us/sample - loss: 0.
2745 - val_loss: 0.2877
Epoch 199/200
2259/2259 [==============================] - 0s 177us/sample - loss: 0.
2653 - val_loss: 0.2881
Epoch 200/200
2259/2259 [==============================] - 0s 178us/sample - loss: 0.
2661 - val_loss: 0.2849
```

Out[45]:
```
<tensorflow.python.keras.callbacks.History at 0x1c507b4890>
```

In [46]:
```
pd.DataFrame(model.history.history)
```

Out[46]:

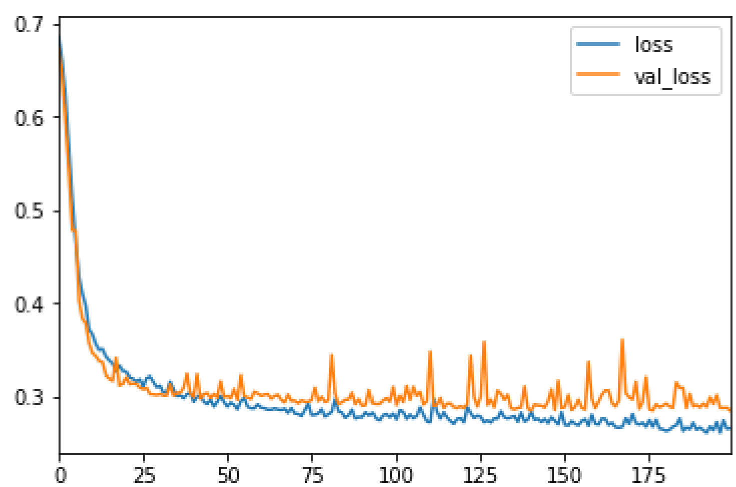
	loss	val_loss
0	0.685922	0.673140
1	0.660124	0.643324
2	0.623214	0.593824
3	0.569316	0.539787
4	0.513984	0.478255
...	...	...
195	0.272631	0.301619
196	0.261124	0.287931
197	0.274488	0.287715
198	0.265250	0.288137
199	0.266122	0.284944

200 rows × 2 columns

Looks like our model performed well and my have some room to be trained a bit more. The Model Reduced the Mean Squared Error accurately based on the Validation Data

In [47]:
```
pd.DataFrame(model.history.history).plot()
```

Out[47]: <matplotlib.axes._subplots.AxesSubplot at 0x1c51815b50>



In [82]:
```
predictions = model.predict_classes(X_test)
```

In [83]:
```
from sklearn.metrics import classification_report,confusion_matrix
```

In [84]:
```
print(classification_report(y_test,predictions))
```

```
              precision    recall  f1-score   support

           0       0.89      0.87      0.88       534
           1       0.85      0.87      0.86       435

    accuracy                           0.87       969
   macro avg       0.87      0.87      0.87       969
weighted avg       0.87      0.87      0.87       969
```

Model has a 87% accuracy -> lets see how it performs when we pass it random data from our dataset .Meaninng we will pass the model data for random days in our data set and see how it performs in classifying VIX as a loss(1 or 0) - (returns < 0) or gain (returns > 0)

In [93]:
```
from random import randint
random_index = randint(0, len(model_data))

new_data = model_data.drop("target", axis=1).iloc[random_index]
new_data
```

Out[93]:
```
UVXY                 72350.000000
SPY                    197.540000
VXXBEN                   0.555000
VIX                     15.980000
UX1                     16.250000
UX2                     16.550000
UX3                     16.750000
UX4                     17.350000
Day of Week              1.000000
Days to Roll            17.000000
Day in Cycle            25.000000
Daily Decay              0.000976
VXXGREG                  1.128285
UX1 % returns            0.058632
UX2 % returns            0.044164
UX3 % returns            0.037152
UX4 % returns            0.029674
UVXY % returns           0.099544
SPY % returns           -0.001819
VXXBEN % returns        -0.445000
regression Slope         0.324000
Inverse Slope           -0.324000
Name: 2014-09-29 00:00:00, dtype: float64
```

In [94]:
```
new_data.shape
```

Out[94]:
```
(22,)
```

We will need to shape the new data to work with the model as well as scale accordingly(our model was trained on scaled data).

In [95]:
```
new_data = new_data.values.reshape(1,22)
```

In [96]:
```
new_data = scalar.transform(new_data)
```

Model Prediction for new data

In [97]:
```
model.predict_classes(new_data)
```

Out[97]:
```
array([[1]], dtype=int32)
```

Prediction Check - True Value

In [99]:
```
new_data_date = model_data.iloc[random_index].name
```

In [250]:
```
vix_data.loc[new_data_date]["target"]
```

Out[250]:
```
1.0
```

lets try a regression Analysis for predicting the Value of VIX

In [102]:
```
vix_reg_data = model_data.drop("target", axis=1)
```

In [104]:
```
X = vix_reg_data.drop("VIX", axis=1).values
y = vix_reg_data["VIX"].values
```

In [105]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30
, random_state=101)
```

Scale Data

In [106]:
```
X_train = scalar.fit_transform(X_train)
```

In [107]:
```
X_test = scalar.transform(X_test)
```

Setting up model

In [108]:
```
X_train.shape
```

Out[108]:
```
(2259, 21)
```

In [109]:
```
model = Sequential()
model.add(Dense(units= 21, activation="relu"))
model.add(Dense(units= 14, activation="relu"))
model.add(Dense(units= 7, activation="relu"))
model.add(Dense(units= 1))
model.compile(optimization = "adam", loss = "mse")
```

In [110]:
```
model.fit(X_train, y_train, validation_data=(X_test,y_test), epochs=200,
batch_size=64)
```

```
Train on 2259 samples, validate on 969 samples
Epoch 1/200
2259/2259 [==============================] - 2s 702us/sample - loss: 39
2.3688 - val_loss: 339.6764
Epoch 2/200
2259/2259 [==============================] - 0s 94us/sample - loss: 24
8.4973 - val_loss: 177.2259
Epoch 3/200
2259/2259 [==============================] - 0s 95us/sample - loss: 11
0.0043 - val_loss: 77.7954
Epoch 4/200
2259/2259 [==============================] - 0s 96us/sample - loss: 63.
1114 - val_loss: 60.1286
Epoch 5/200
2259/2259 [==============================] - 0s 92us/sample - loss: 48.
5851 - val_loss: 43.6795
Epoch 6/200
2259/2259 [==============================] - 0s 95us/sample - loss: 33.
0247 - val_loss: 26.8251
Epoch 7/200
2259/2259 [==============================] - 0s 93us/sample - loss: 18.
9317 - val_loss: 13.1247
Epoch 8/200
2259/2259 [==============================] - 0s 95us/sample - loss: 8.7
904 - val_loss: 5.7687
Epoch 9/200
2259/2259 [==============================] - 0s 92us/sample - loss: 4.7
346 - val_loss: 3.3921
Epoch 10/200
2259/2259 [==============================] - 0s 94us/sample - loss: 3.5
343 - val_loss: 2.6503
Epoch 11/200
2259/2259 [==============================] - 0s 111us/sample - loss: 2.
8106 - val_loss: 2.2804
Epoch 12/200
2259/2259 [==============================] - 0s 94us/sample - loss: 2.4
066 - val_loss: 1.7053
Epoch 13/200
2259/2259 [==============================] - 0s 93us/sample - loss: 2.0
057 - val_loss: 1.8347
Epoch 14/200
2259/2259 [==============================] - 0s 95us/sample - loss: 1.7
713 - val_loss: 1.5533
Epoch 15/200
2259/2259 [==============================] - 0s 95us/sample - loss: 1.5
760 - val_loss: 1.0900
Epoch 16/200
2259/2259 [==============================] - 0s 91us/sample - loss: 1.3
941 - val_loss: 0.9962
Epoch 17/200
2259/2259 [==============================] - 0s 91us/sample - loss: 1.2
241 - val_loss: 1.1484
Epoch 18/200
2259/2259 [==============================] - 0s 92us/sample - loss: 1.0
323 - val_loss: 0.7293
Epoch 19/200
2259/2259 [==============================] - 0s 91us/sample - loss: 0.8
```

```
516 - val_loss: 1.4577
Epoch 20/200
2259/2259 [==============================] - 0s 92us/sample - loss: 0.7
357 - val_loss: 0.6957
Epoch 21/200
2259/2259 [==============================] - 0s 92us/sample - loss: 0.6
512 - val_loss: 0.4155
Epoch 22/200
2259/2259 [==============================] - 0s 91us/sample - loss: 0.5
587 - val_loss: 0.4846
Epoch 23/200
2259/2259 [==============================] - 0s 91us/sample - loss: 0.4
680 - val_loss: 0.3310
Epoch 24/200
2259/2259 [==============================] - 0s 92us/sample - loss: 0.4
204 - val_loss: 0.2833
Epoch 25/200
2259/2259 [==============================] - 0s 103us/sample - loss: 0.
3743 - val_loss: 0.2535
Epoch 26/200
2259/2259 [==============================] - 0s 92us/sample - loss: 0.3
132 - val_loss: 0.3339
Epoch 27/200
2259/2259 [==============================] - 0s 95us/sample - loss: 0.3
242 - val_loss: 0.2176
Epoch 28/200
2259/2259 [==============================] - 0s 95us/sample - loss: 0.2
818 - val_loss: 0.2097
Epoch 29/200
2259/2259 [==============================] - 0s 95us/sample - loss: 0.2
698 - val_loss: 0.6849
Epoch 30/200
2259/2259 [==============================] - 0s 91us/sample - loss: 0.2
539 - val_loss: 0.2103
Epoch 31/200
2259/2259 [==============================] - 0s 91us/sample - loss: 0.2
513 - val_loss: 0.3249
Epoch 32/200
2259/2259 [==============================] - 0s 92us/sample - loss: 0.2
501 - val_loss: 0.2107
Epoch 33/200
2259/2259 [==============================] - 0s 92us/sample - loss: 0.2
305 - val_loss: 0.1784
Epoch 34/200
2259/2259 [==============================] - 0s 91us/sample - loss: 0.2
195 - val_loss: 0.1708
Epoch 35/200
2259/2259 [==============================] - 0s 91us/sample - loss: 0.2
210 - val_loss: 0.2417
Epoch 36/200
2259/2259 [==============================] - 0s 92us/sample - loss: 0.2
166 - val_loss: 0.2285
Epoch 37/200
2259/2259 [==============================] - 0s 92us/sample - loss: 0.2
051 - val_loss: 0.4840
Epoch 38/200
2259/2259 [==============================] - 0s 93us/sample - loss: 0.2
```

```
092 - val_loss: 0.1608
Epoch 39/200
2259/2259 [==============================] - 0s 91us/sample - loss: 0.1
975 - val_loss: 0.1941
Epoch 40/200
2259/2259 [==============================] - 0s 93us/sample - loss: 0.1
827 - val_loss: 0.1359
Epoch 41/200
2259/2259 [==============================] - 0s 93us/sample - loss: 0.1
935 - val_loss: 0.2960
Epoch 42/200
2259/2259 [==============================] - 0s 93us/sample - loss: 0.1
936 - val_loss: 0.2240
Epoch 43/200
2259/2259 [==============================] - 0s 93us/sample - loss: 0.1
952 - val_loss: 0.2687
Epoch 44/200
2259/2259 [==============================] - 0s 92us/sample - loss: 0.1
862 - val_loss: 0.1419
Epoch 45/200
2259/2259 [==============================] - 0s 92us/sample - loss: 0.1
770 - val_loss: 0.1969
Epoch 46/200
2259/2259 [==============================] - 0s 95us/sample - loss: 0.1
900 - val_loss: 0.1410
Epoch 47/200
2259/2259 [==============================] - 0s 92us/sample - loss: 0.1
754 - val_loss: 0.3223
Epoch 48/200
2259/2259 [==============================] - 0s 95us/sample - loss: 0.1
680 - val_loss: 0.4169
Epoch 49/200
2259/2259 [==============================] - 0s 93us/sample - loss: 0.1
665 - val_loss: 0.6828
Epoch 50/200
2259/2259 [==============================] - 0s 96us/sample - loss: 0.1
591 - val_loss: 0.1255
Epoch 51/200
2259/2259 [==============================] - 0s 92us/sample - loss: 0.1
756 - val_loss: 0.1566
Epoch 52/200
2259/2259 [==============================] - 0s 102us/sample - loss: 0.
1556 - val_loss: 0.1871
Epoch 53/200
2259/2259 [==============================] - 0s 118us/sample - loss: 0.
1564 - val_loss: 0.1049
Epoch 54/200
2259/2259 [==============================] - 0s 97us/sample - loss: 0.1
645 - val_loss: 0.1843
Epoch 55/200
2259/2259 [==============================] - 0s 91us/sample - loss: 0.1
549 - val_loss: 0.3140
Epoch 56/200
2259/2259 [==============================] - 0s 93us/sample - loss: 0.1
601 - val_loss: 0.1420
Epoch 57/200
2259/2259 [==============================] - 0s 98us/sample - loss: 0.1
```

```
340 - val_loss: 0.3635
Epoch 58/200
2259/2259 [==============================] - 0s 94us/sample - loss: 0.1
730 - val_loss: 0.0959
Epoch 59/200
2259/2259 [==============================] - 0s 92us/sample - loss: 0.1
420 - val_loss: 0.1160
Epoch 60/200
2259/2259 [==============================] - 0s 91us/sample - loss: 0.1
521 - val_loss: 0.1152
Epoch 61/200
2259/2259 [==============================] - 0s 92us/sample - loss: 0.1
437 - val_loss: 0.3880
Epoch 62/200
2259/2259 [==============================] - 0s 96us/sample - loss: 0.1
394 - val_loss: 0.1420
Epoch 63/200
2259/2259 [==============================] - 0s 93us/sample - loss: 0.1
402 - val_loss: 0.1022
Epoch 64/200
2259/2259 [==============================] - 0s 94us/sample - loss: 0.1
567 - val_loss: 0.0869
Epoch 65/200
2259/2259 [==============================] - 0s 95us/sample - loss: 0.1
301 - val_loss: 0.1212
Epoch 66/200
2259/2259 [==============================] - 0s 91us/sample - loss: 0.1
481 - val_loss: 0.1784
Epoch 67/200
2259/2259 [==============================] - 0s 93us/sample - loss: 0.1
416 - val_loss: 0.1780
Epoch 68/200
2259/2259 [==============================] - 0s 92us/sample - loss: 0.1
324 - val_loss: 0.1119
Epoch 69/200
2259/2259 [==============================] - 0s 90us/sample - loss: 0.1
375 - val_loss: 0.1141
Epoch 70/200
2259/2259 [==============================] - 0s 100us/sample - loss: 0.
1352 - val_loss: 0.2120
Epoch 71/200
2259/2259 [==============================] - 0s 98us/sample - loss: 0.1
325 - val_loss: 0.1884
Epoch 72/200
2259/2259 [==============================] - 0s 92us/sample - loss: 0.1
274 - val_loss: 0.0962
Epoch 73/200
2259/2259 [==============================] - 0s 94us/sample - loss: 0.1
464 - val_loss: 0.0860
Epoch 74/200
2259/2259 [==============================] - 0s 94us/sample - loss: 0.1
220 - val_loss: 0.1490
Epoch 75/200
2259/2259 [==============================] - 0s 100us/sample - loss: 0.
1376 - val_loss: 0.2622
Epoch 76/200
2259/2259 [==============================] - 0s 93us/sample - loss: 0.1
```

```
302 - val_loss: 0.2369
Epoch 77/200
2259/2259 [==============================] - 0s 90us/sample - loss: 0.1
433 - val_loss: 0.0807
Epoch 78/200
2259/2259 [==============================] - 0s 91us/sample - loss: 0.1
254 - val_loss: 0.1961
Epoch 79/200
2259/2259 [==============================] - 0s 93us/sample - loss: 0.1
430 - val_loss: 0.1682
Epoch 80/200
2259/2259 [==============================] - 0s 96us/sample - loss: 0.1
215 - val_loss: 0.1139
Epoch 81/200
2259/2259 [==============================] - 0s 100us/sample - loss: 0.
1414 - val_loss: 0.0763
Epoch 82/200
2259/2259 [==============================] - 0s 91us/sample - loss: 0.1
219 - val_loss: 0.1252
Epoch 83/200
2259/2259 [==============================] - 0s 88us/sample - loss: 0.1
236 - val_loss: 0.2080
Epoch 84/200
2259/2259 [==============================] - 0s 103us/sample - loss: 0.
1312 - val_loss: 0.0690
Epoch 85/200
2259/2259 [==============================] - 0s 95us/sample - loss: 0.1
244 - val_loss: 0.3409
Epoch 86/200
2259/2259 [==============================] - 0s 89us/sample - loss: 0.1
275 - val_loss: 0.1805
Epoch 87/200
2259/2259 [==============================] - 0s 92us/sample - loss: 0.1
076 - val_loss: 0.0676
Epoch 88/200
2259/2259 [==============================] - 0s 103us/sample - loss: 0.
1358 - val_loss: 0.1194
Epoch 89/200
2259/2259 [==============================] - 0s 103us/sample - loss: 0.
1286 - val_loss: 0.1654
Epoch 90/200
2259/2259 [==============================] - 0s 100us/sample - loss: 0.
1328 - val_loss: 0.1541
Epoch 91/200
2259/2259 [==============================] - 0s 97us/sample - loss: 0.1
138 - val_loss: 0.0734
Epoch 92/200
2259/2259 [==============================] - 0s 97us/sample - loss: 0.1
203 - val_loss: 0.0658
Epoch 93/200
2259/2259 [==============================] - 0s 94us/sample - loss: 0.1
256 - val_loss: 0.1225
Epoch 94/200
2259/2259 [==============================] - 0s 93us/sample - loss: 0.1
147 - val_loss: 0.0634
Epoch 95/200
2259/2259 [==============================] - 0s 101us/sample - loss: 0.
```

```
1279 - val_loss: 0.0765
Epoch 96/200
2259/2259 [==============================] - 0s 101us/sample - loss: 0.
1170 - val_loss: 0.3416
Epoch 97/200
2259/2259 [==============================] - 0s 92us/sample - loss: 0.1
271 - val_loss: 0.0646
Epoch 98/200
2259/2259 [==============================] - 0s 90us/sample - loss: 0.1
102 - val_loss: 0.1850
Epoch 99/200
2259/2259 [==============================] - 0s 94us/sample - loss: 0.1
158 - val_loss: 0.1242
Epoch 100/200
2259/2259 [==============================] - 0s 93us/sample - loss: 0.1
220 - val_loss: 0.2494
Epoch 101/200
2259/2259 [==============================] - 0s 90us/sample - loss: 0.1
145 - val_loss: 0.1148
Epoch 102/200
2259/2259 [==============================] - 0s 92us/sample - loss: 0.1
247 - val_loss: 0.0652
Epoch 103/200
2259/2259 [==============================] - 0s 98us/sample - loss: 0.1
077 - val_loss: 0.0727
Epoch 104/200
2259/2259 [==============================] - 0s 93us/sample - loss: 0.1
263 - val_loss: 0.0580
Epoch 105/200
2259/2259 [==============================] - 0s 92us/sample - loss: 0.1
135 - val_loss: 0.1024
Epoch 106/200
2259/2259 [==============================] - 0s 92us/sample - loss: 0.1
178 - val_loss: 0.0949
Epoch 107/200
2259/2259 [==============================] - 0s 94us/sample - loss: 0.1
100 - val_loss: 0.0880
Epoch 108/200
2259/2259 [==============================] - 0s 91us/sample - loss: 0.1
237 - val_loss: 0.0883
Epoch 109/200
2259/2259 [==============================] - 0s 90us/sample - loss: 0.1
157 - val_loss: 0.1715
Epoch 110/200
2259/2259 [==============================] - 0s 91us/sample - loss: 0.1
077 - val_loss: 0.0675
Epoch 111/200
2259/2259 [==============================] - 0s 91us/sample - loss: 0.1
128 - val_loss: 0.1421
Epoch 112/200
2259/2259 [==============================] - 0s 91us/sample - loss: 0.1
153 - val_loss: 0.0808
Epoch 113/200
2259/2259 [==============================] - 0s 89us/sample - loss: 0.1
162 - val_loss: 0.1834
Epoch 114/200
2259/2259 [==============================] - 0s 93us/sample - loss: 0.1
```

```
046 - val_loss: 0.3275
Epoch 115/200
2259/2259 [==============================] - 0s 92us/sample - loss: 0.1
202 - val_loss: 0.0627
Epoch 116/200
2259/2259 [==============================] - 0s 92us/sample - loss: 0.1
087 - val_loss: 0.1246
Epoch 117/200
2259/2259 [==============================] - 0s 90us/sample - loss: 0.1
071 - val_loss: 0.4103
Epoch 118/200
2259/2259 [==============================] - 0s 92us/sample - loss: 0.1
234 - val_loss: 0.0715
Epoch 119/200
2259/2259 [==============================] - 0s 92us/sample - loss: 0.1
023 - val_loss: 0.0617
Epoch 120/200
2259/2259 [==============================] - 0s 92us/sample - loss: 0.1
097 - val_loss: 0.1635
Epoch 121/200
2259/2259 [==============================] - 0s 91us/sample - loss: 0.1
086 - val_loss: 0.1660
Epoch 122/200
2259/2259 [==============================] - 0s 93us/sample - loss: 0.1
196 - val_loss: 0.0651
Epoch 123/200
2259/2259 [==============================] - 0s 93us/sample - loss: 0.1
115 - val_loss: 0.0821
Epoch 124/200
2259/2259 [==============================] - 0s 92us/sample - loss: 0.1
116 - val_loss: 0.0538
Epoch 125/200
2259/2259 [==============================] - 0s 100us/sample - loss: 0.
1026 - val_loss: 0.1082
Epoch 126/200
2259/2259 [==============================] - 0s 92us/sample - loss: 0.1
167 - val_loss: 0.0569
Epoch 127/200
2259/2259 [==============================] - 0s 93us/sample - loss: 0.1
092 - val_loss: 0.2217
Epoch 128/200
2259/2259 [==============================] - 0s 93us/sample - loss: 0.1
110 - val_loss: 0.4066
Epoch 129/200
2259/2259 [==============================] - 0s 91us/sample - loss: 0.1
037 - val_loss: 0.0577
Epoch 130/200
2259/2259 [==============================] - 0s 93us/sample - loss: 0.1
164 - val_loss: 0.4164
Epoch 131/200
2259/2259 [==============================] - 0s 94us/sample - loss: 0.1
033 - val_loss: 0.1091
Epoch 132/200
2259/2259 [==============================] - 0s 95us/sample - loss: 0.1
002 - val_loss: 0.1349
Epoch 133/200
2259/2259 [==============================] - 0s 103us/sample - loss: 0.
```

```
1027 - val_loss: 0.1483
Epoch 134/200
2259/2259 [==============================] - 0s 102us/sample - loss: 0.
1051 - val_loss: 0.0708
Epoch 135/200
2259/2259 [==============================] - 0s 97us/sample - loss: 0.0
869 - val_loss: 0.2519
Epoch 136/200
2259/2259 [==============================] - 0s 98us/sample - loss: 0.1
173 - val_loss: 0.2991
Epoch 137/200
2259/2259 [==============================] - 0s 102us/sample - loss: 0.
1065 - val_loss: 0.0630
Epoch 138/200
2259/2259 [==============================] - 0s 91us/sample - loss: 0.1
061 - val_loss: 0.0912
Epoch 139/200
2259/2259 [==============================] - 0s 93us/sample - loss: 0.1
152 - val_loss: 0.1375
Epoch 140/200
2259/2259 [==============================] - 0s 94us/sample - loss: 0.1
083 - val_loss: 0.0625
Epoch 141/200
2259/2259 [==============================] - 0s 92us/sample - loss: 0.0
806 - val_loss: 0.0620
Epoch 142/200
2259/2259 [==============================] - 0s 92us/sample - loss: 0.1
218 - val_loss: 0.0897
Epoch 143/200
2259/2259 [==============================] - 0s 97us/sample - loss: 0.1
054 - val_loss: 0.1913
Epoch 144/200
2259/2259 [==============================] - 0s 97us/sample - loss: 0.0
960 - val_loss: 0.3131
Epoch 145/200
2259/2259 [==============================] - 0s 96us/sample - loss: 0.1
066 - val_loss: 0.1214
Epoch 146/200
2259/2259 [==============================] - 0s 93us/sample - loss: 0.1
067 - val_loss: 0.0922
Epoch 147/200
2259/2259 [==============================] - 0s 98us/sample - loss: 0.1
105 - val_loss: 0.0817
Epoch 148/200
2259/2259 [==============================] - 0s 94us/sample - loss: 0.0
982 - val_loss: 0.1575
Epoch 149/200
2259/2259 [==============================] - 0s 94us/sample - loss: 0.0
967 - val_loss: 0.0643
Epoch 150/200
2259/2259 [==============================] - 0s 93us/sample - loss: 0.1
119 - val_loss: 0.0940
Epoch 151/200
2259/2259 [==============================] - 0s 90us/sample - loss: 0.0
945 - val_loss: 0.0724
Epoch 152/200
2259/2259 [==============================] - 0s 91us/sample - loss: 0.1
```

```
125 - val_loss: 0.1093
Epoch 153/200
2259/2259 [==============================] - 0s 89us/sample - loss: 0.1
076 - val_loss: 0.0521
Epoch 154/200
2259/2259 [==============================] - 0s 89us/sample - loss: 0.0
996 - val_loss: 0.0481
Epoch 155/200
2259/2259 [==============================] - 0s 90us/sample - loss: 0.1
000 - val_loss: 0.0754
Epoch 156/200
2259/2259 [==============================] - 0s 89us/sample - loss: 0.1
014 - val_loss: 0.1616
Epoch 157/200
2259/2259 [==============================] - 0s 89us/sample - loss: 0.1
021 - val_loss: 0.0632
Epoch 158/200
2259/2259 [==============================] - 0s 88us/sample - loss: 0.1
058 - val_loss: 0.0637
Epoch 159/200
2259/2259 [==============================] - 0s 90us/sample - loss: 0.1
023 - val_loss: 0.0495
Epoch 160/200
2259/2259 [==============================] - 0s 89us/sample - loss: 0.0
839 - val_loss: 0.0476
Epoch 161/200
2259/2259 [==============================] - 0s 87us/sample - loss: 0.1
004 - val_loss: 0.0597
Epoch 162/200
2259/2259 [==============================] - 0s 89us/sample - loss: 0.1
045 - val_loss: 0.1908
Epoch 163/200
2259/2259 [==============================] - 0s 89us/sample - loss: 0.0
969 - val_loss: 0.0948
Epoch 164/200
2259/2259 [==============================] - 0s 89us/sample - loss: 0.1
048 - val_loss: 0.0798
Epoch 165/200
2259/2259 [==============================] - 0s 89us/sample - loss: 0.0
987 - val_loss: 0.4313
Epoch 166/200
2259/2259 [==============================] - 0s 111us/sample - loss: 0.
1098 - val_loss: 0.2474
Epoch 167/200
2259/2259 [==============================] - 0s 102us/sample - loss: 0.
0911 - val_loss: 0.1299
Epoch 168/200
2259/2259 [==============================] - 0s 97us/sample - loss: 0.1
034 - val_loss: 0.0770
Epoch 169/200
2259/2259 [==============================] - 0s 98us/sample - loss: 0.0
923 - val_loss: 0.0461
Epoch 170/200
2259/2259 [==============================] - 0s 93us/sample - loss: 0.1
094 - val_loss: 0.0627
Epoch 171/200
2259/2259 [==============================] - 0s 90us/sample - loss: 0.0
```

```
930 - val_loss: 0.2059
Epoch 172/200
2259/2259 [==============================] - 0s 89us/sample - loss: 0.0
998 - val_loss: 0.0915
Epoch 173/200
2259/2259 [==============================] - 0s 94us/sample - loss: 0.0
938 - val_loss: 0.1886
Epoch 174/200
2259/2259 [==============================] - 0s 92us/sample - loss: 0.0
957 - val_loss: 0.3766
Epoch 175/200
2259/2259 [==============================] - 0s 92us/sample - loss: 0.1
080 - val_loss: 0.0854
Epoch 176/200
2259/2259 [==============================] - 0s 90us/sample - loss: 0.1
034 - val_loss: 0.0975
Epoch 177/200
2259/2259 [==============================] - 0s 89us/sample - loss: 0.0
946 - val_loss: 0.1315
Epoch 178/200
2259/2259 [==============================] - 0s 86us/sample - loss: 0.1
014 - val_loss: 0.0811
Epoch 179/200
2259/2259 [==============================] - 0s 88us/sample - loss: 0.0
959 - val_loss: 0.0604
Epoch 180/200
2259/2259 [==============================] - 0s 87us/sample - loss: 0.0
978 - val_loss: 0.1490
Epoch 181/200
2259/2259 [==============================] - 0s 88us/sample - loss: 0.1
087 - val_loss: 0.0584
Epoch 182/200
2259/2259 [==============================] - 0s 86us/sample - loss: 0.0
882 - val_loss: 0.1065
Epoch 183/200
2259/2259 [==============================] - 0s 87us/sample - loss: 0.1
022 - val_loss: 0.0576
Epoch 184/200
2259/2259 [==============================] - 0s 87us/sample - loss: 0.1
017 - val_loss: 0.1545
Epoch 185/200
2259/2259 [==============================] - 0s 90us/sample - loss: 0.0
935 - val_loss: 0.0535
Epoch 186/200
2259/2259 [==============================] - 0s 87us/sample - loss: 0.0
883 - val_loss: 0.0437
Epoch 187/200
2259/2259 [==============================] - 0s 85us/sample - loss: 0.1
043 - val_loss: 0.0564
Epoch 188/200
2259/2259 [==============================] - 0s 84us/sample - loss: 0.0
950 - val_loss: 0.0513
Epoch 189/200
2259/2259 [==============================] - 0s 87us/sample - loss: 0.0
931 - val_loss: 0.0809
Epoch 190/200
2259/2259 [==============================] - 0s 88us/sample - loss: 0.0
```

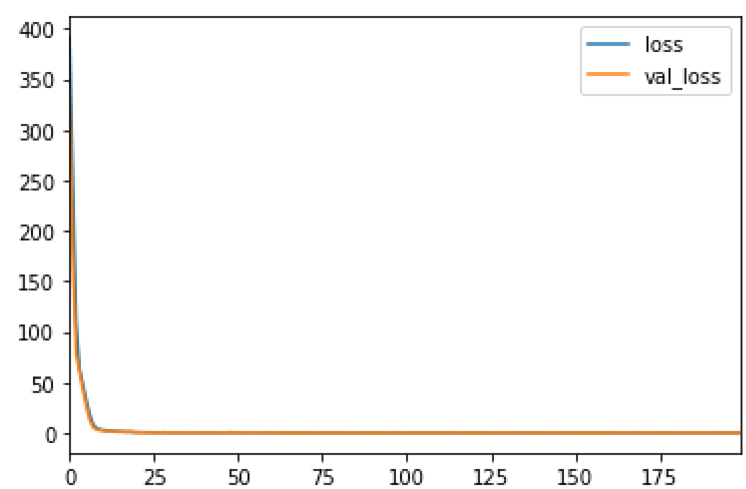
```
936 - val_loss: 0.2134
Epoch 191/200
2259/2259 [==============================] - 0s 89us/sample - loss: 0.0
962 - val_loss: 0.0447
Epoch 192/200
2259/2259 [==============================] - 0s 89us/sample - loss: 0.0
934 - val_loss: 0.0910
Epoch 193/200
2259/2259 [==============================] - 0s 88us/sample - loss: 0.0
980 - val_loss: 0.0845
Epoch 194/200
2259/2259 [==============================] - 0s 86us/sample - loss: 0.0
983 - val_loss: 0.0449
Epoch 195/200
2259/2259 [==============================] - 0s 86us/sample - loss: 0.0
877 - val_loss: 0.1142
Epoch 196/200
2259/2259 [==============================] - 0s 86us/sample - loss: 0.0
930 - val_loss: 0.2338
Epoch 197/200
2259/2259 [==============================] - 0s 85us/sample - loss: 0.0
965 - val_loss: 0.1436
Epoch 198/200
2259/2259 [==============================] - 0s 86us/sample - loss: 0.0
904 - val_loss: 0.1274
Epoch 199/200
2259/2259 [==============================] - 0s 86us/sample - loss: 0.0
916 - val_loss: 0.0526
Epoch 200/200
2259/2259 [==============================] - 0s 87us/sample - loss: 0.1
001 - val_loss: 0.1257
```

Out[110]: <tensorflow.python.keras.callbacks.History at 0x1c51f773d0>

Mode looks like it performed well and still has room to be trained

In [112]:
```
pd.DataFrame(model.history.history).plot()
```

Out[112]: <matplotlib.axes._subplots.AxesSubplot at 0x1c52f78e50>



We will look at the predictions of the model

In [213]:
```
predict = model.predict(X_test)
```

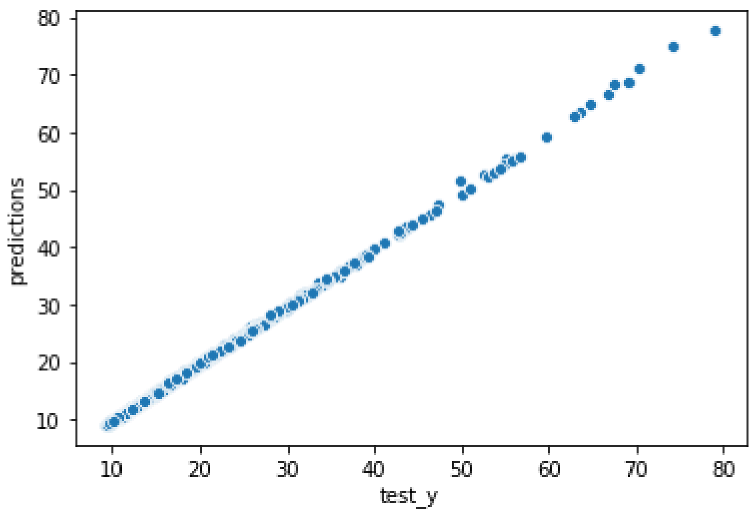
lets take a look at the predictions with a scatter plot

In [214]:
```
test_and_pred = pd.DataFrame(y_test, columns=["test_y"])
```

In [215]:
```
test_and_pred["predictions"] = predict
```

In [216]:
```
sns.scatterplot(x = "test_y", y = "predictions", data=test_and_pred)
```

Out[216]: <matplotlib.axes._subplots.AxesSubplot at 0x1c6bc17b50>



Error Plot

In [217]:
```
from sklearn.metrics import mean_absolute_error, mean_squared_error, exp
lained_variance_score
```

In [218]:
```
mean_absolute_error(y_test,predict)
```

Out[218]: 0.31341387596169745

In [219]:
```
mean_squared_error(y_test, predict)
```

Out[219]: 0.1257336015074917

lets see how much variance is being explained by our model

- This is a very good explained variance-> meaning 99% of the variance in our data is explained by the model

In [220]:
```
explained_variance_score(y_test,predict)
```

Out[220]:
```
0.9995422662157213
```

lets test this and try to predict the value of VIX on a given Day

In [251]:
```
from random import randint
inde = randint(0, len(vix_reg_data))
new_data = vix_reg_data.drop("VIX", axis=1).iloc[inde]
new_data
```

Out[251]:
```
UVXY                  5.330000e+06
SPY                   1.419900e+02
VXXBEN                3.840000e+00
UX1                   1.590000e+01
UX2                   1.875000e+01
UX3                   2.070000e+01
UX4                   2.225000e+01
Day of Week           4.000000e+00
Days to Roll          4.000000e+00
Day in Cycle          2.500000e+01
Daily Decay           1.499342e-02
VXXGREG               7.854444e+00
UX1 % returns        -1.851852e-02
UX2 % returns        -1.315789e-02
UX3 % returns        -1.193317e-02
UX4 % returns        -1.111111e-02
UVXY % returns       -3.963964e-02
SPY % returns         7.378503e-03
VXXBEN % returns      2.263648e-02
regression Slope      2.072000e+00
Inverse Slope        -2.072000e+00
Name: 2012-08-16 00:00:00, dtype: float64
```

In [252]:
```
len(new_data.values)
```

Out[252]:
```
21
```

In [253]:
```
vix_date = vix_reg_data.iloc[inde].name
vix_date
```

Out[253]:
```
Timestamp('2012-08-16 00:00:00')
```

In [254]:
```
new_data = scalar.transform(new_data.values.reshape(1,21))
```

Model Predicts VIX will be priced (AdJ CLose)

In [255]:
```
model.predict(new_data)
```

Out[255]:
```
array([[13.828726]], dtype=float32)
```

True Value

In [256]:
```
vix_reg_data.loc[vix_date]['VIX']
```

Out[256]:
```
14.29
```

Error plot

In [257]:
```
y_test.shape
```

Out[257]:
```
(969,)
```

In [258]:
```
predict.shape
```

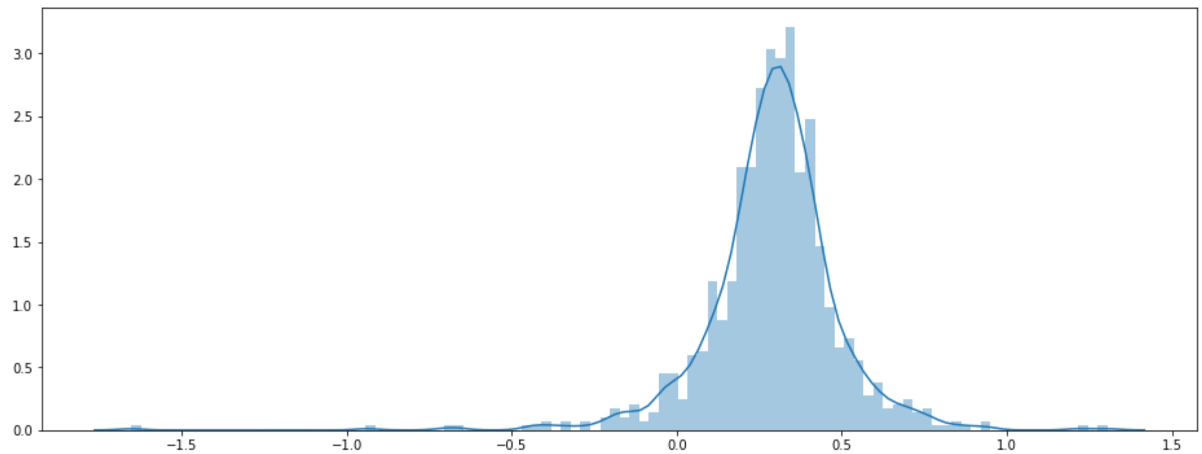
Out[258]:
```
(969, 1)
```

Model make a solid predicition

- with most of the error occurring between 0 and 0.5

In [259]:
```
plt.figure(figsize=(16,6))
sns.distplot(y_test - predict.reshape(1,969), bins = 100)
```

Out[259]: <matplotlib.axes._subplots.AxesSubplot at 0x1c6aeb2910>



In [ ]:

In [ ]: