Building the Ensemble Model

Packages

In [1]:
```
### Data Handling & Helpers
import pandas as pd
import numpy as np
import pandas_ta as ta

### Plotting
import seaborn as sns
import matplotlib.pyplot as plt
from matplotlib.ticker import PercentFormatter

### Processing
from sklearn.decomposition import PCA
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import train_test_split

### Models
from sklearn.svm import SVC
from sklearn.ensemble import VotingClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier

### Model Evaluation
from sklearn.metrics import confusion_matrix
from sklearn.metrics import ConfusionMatrixDisplay
from sklearn.model_selection import cross_val_score
```

Function Space

In [105]:
```python
# Pie chart
def pie_chart(dataset, **kwargs):
    labels = '-1', '1', '0'
    sizes = [(len(dataset[dataset==-1])/len(dataset)),
             (len(dataset[dataset==1])/len(dataset)),
             (len(dataset[dataset==0])/len(dataset))]

    fig1, ax1 = plt.subplots()
    ax1.pie(sizes, labels=labels, autopct='%1.1f%%', shadow=True)
    ax1.axis('equal')
    if "title" in kwargs: ax1.set_title(kwargs["title"])
    plt.show()

# Method for Creating past data as Xtraini and Xtest as recent data
def create_timeseries_split(dataframe, test_size):
    stop = int(len(dataframe) * (1-test_size));

    Train =  dataframe.iloc[0:stop]
    Test = dataframe.iloc[stop+1:-1]

    Xtrain = Train.drop(columns="Target")
    ytrain = Train.Target

    Xtest = Test.drop(columns="Target")
    ytest = Test.Target

    return Xtrain, Xtest, ytrain, ytest

# Sklearn method for creating training and test data sets
def create_splits(X, y, rnd_state=2, test_size=0.30):
    return train_test_split(X, y, test_size=test_size, random_state=rnd_state)

def target_helper(y_pred, y_testp, SP500, test_size):
    SP500.ta.ema(length = 30, append=True)
    SP500["EMA_30_FT"] = SP500.EMA_30.shift(periods=-30)
    SP500["Diff"] = (SP500.EMA_30_FT - SP500.EMA_30)
    SP500["Diff_ratio"] = SP500.Diff / SP500.EMA_30
    SP500["Diff_shift"] = SP500.Diff_ratio.shift(periods=-30)
    SP500["Target"] = SP500.Diff_shift.apply(lambda x: -1 if x < -0.01 else (1 if
    SP500["Pred"] = y_pred
    return SP500
```

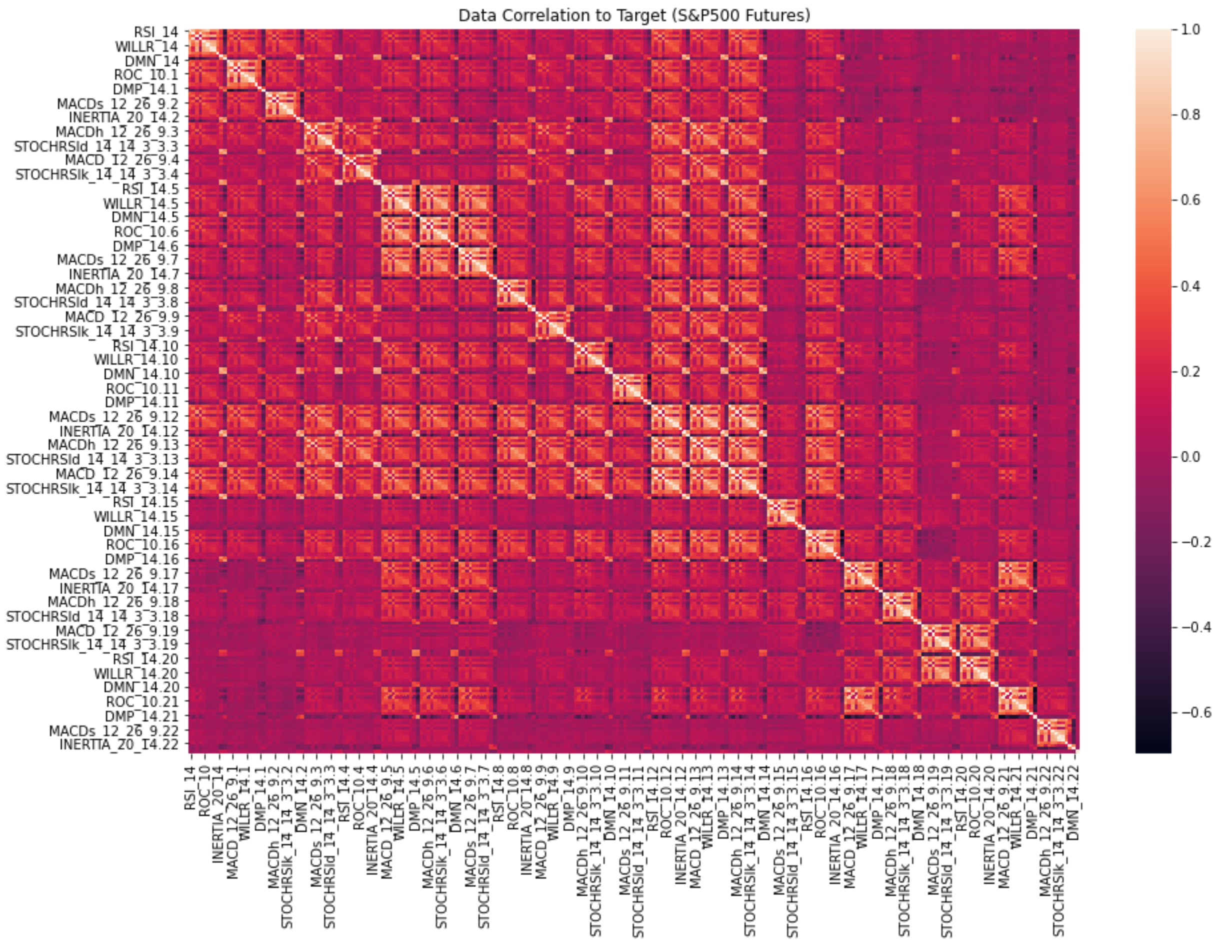
Import the Data

In [3]:
```python
dataframe = pd.read_csv(r"data/momentum_market_data.csv", index_col="Date")
# dataframe.head(5)
```

Process the Data

As expected there are not issues with the dataset. No multi-colinearity so the models should do fine. All values are oscillators so finding boundaries should be easier for the models.

In [4]:
```python
plt.figure(figsize=(15,10))
sns.heatmap(dataframe.corr())
plt.xlabel('')
plt.ylabel('')
plt.title('Data Correlation to Target (S&P500 Futures)')
fig.savefig(r"figures\DataCorrelationPlot.png", dpi=600)
plt.show()
```



Here I'm making 3 sets of data. One for training the model, another for testing the model, and another for testing the model predictions in a forward intime capacity. *Note: I'm not certain this is the most efficient way to achieve high performance.*

In [24]:
```
train_and_test = create_timeseries_split(dataframe, test_size=0.10)
Xtrain =train_and_test[0].to_numpy()
Xtest_ft =train_and_test[1].to_numpy()
ytrain = train_and_test[2].to_numpy()
ytest_ft = train_and_test[3].to_numpy()
X_train, X_test, y_train, y_test = create_splits(Xtrain, ytrain)

print(f'Training sample: [{X_train.shape}, {y_train.shape}], ({type(X_train)}, {t
print(f'Train Test sample: [{X_test.shape}, {y_test.shape}], ({type(X_test)}, {ty
print(f'Test sample: [{Xtest_ft.shape}, {ytest_ft.shape}], ({type(Xtest_ft)}, {ty
```

```
Training sample: [(2910, 253), (2910,)], (<class 'numpy.ndarray'>, <class 'nump
y.ndarray'>)
Train Test sample: [(1248, 253), (1248,)], (<class 'numpy.ndarray'>, <class 'nu
mpy.ndarray'>)
Test sample: [(460, 253), (460,)], (<class 'numpy.ndarray'>, <class 'numpy.ndar
ray'>)
```

Gathering the Models

- Running Grid-Search again, because the dataset is much larger now, and the models might prefer some differently tuned hyperparameters.
- Gathering the best estimators and using those into the ensemble
- Using a soft voting class ensemble to generate final target

Support Vector Machine Classifier (SVC)

In [6]:
```
svm_m = modeling_pipeline = Pipeline([('scaling', StandardScaler()),
                                      ('pca', PCA()),
                                      ('model', SVC()),
                                      ])

param_grid = [{'model__C': [1, 10, 100, 1000],
              'pca__n_components': [None,1,5,10,15],
              'model__kernel': ['rbf'],
              'model__probability':[True]
             }]

scoring = ['f1_macro', 'roc_auc_ovo']

svm_results = GridSearchCV(estimator=svm_m, param_grid=param_grid, scoring=scor
svm_results = svm_results.fit(X_train, y_train)
```

In [7]:
```
# svm_score = svm_results.best_score_
print(f'Support Vector Machine Score: {svm_results.best_score_:.2%}')
print(svm_results.best_estimator_, svm_results.best_params_)
svm = svm_results.best_estimator_
```

```
Support Vector Machine Score: 98.94%
Pipeline(steps=[('scaling', StandardScaler()), ('pca', PCA()),
                ('model', SVC(C=10, probability=True))]) {'model__C': 10, 'mode
l__kernel': 'rbf', 'model__probability': True, 'pca__n_components': None}
```

In [8]:
```
from sklearn.metrics import classification_report
y_pred = svm.predict(X_test)
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

        -1.0       0.97      0.95      0.96       312
         0.0       0.90      0.91      0.91       253
         1.0       0.98      0.99      0.98       683

    accuracy                           0.96      1248
   macro avg       0.95      0.95      0.95      1248
weighted avg       0.96      0.96      0.96      1248
```

K-Nearest Neighbors (KNN)

In [9]:
```
knn_m = modeling_pipeline = Pipeline([('scaling', StandardScaler()),
                                      ('pca', PCA(n_components=None)),
                                      ('model', KNeighborsClassifier())])



param_grid = [
  {'model__n_neighbors': [1, 4, 8, 10, 15],
   'pca__n_components': [None,1,2,3,4,5,10,15],
   'model__weights': ['uniform','distance']}
 ]

knn_results = GridSearchCV(estimator=knn_m, param_grid=param_grid, scoring=scorin
knn_results = knn_results.fit(X_train, y_train)
```

In [10]:
```
knn_score = knn_results.score(X_test, y_test)
print(f'k-Nearest Neighbor Score: {knn_score:.2%}')
print(knn_results.best_estimator_)
```

```
k-Nearest Neighbor Score: 99.32%
Pipeline(steps=[('scaling', StandardScaler()), ('pca', PCA()),
                ('model',
                 KNeighborsClassifier(n_neighbors=4, weights='distance'))])
```

In [107]:
```
from sklearn.metrics import classification_report
y_pred = knn_results.predict(X_test)
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

        -1.0       0.96      0.95      0.96       312
         0.0       0.87      0.90      0.88       253
         1.0       0.98      0.98      0.98       683

    accuracy                           0.95      1248
   macro avg       0.94      0.94      0.94      1248
weighted avg       0.95      0.95      0.95      1248
```

Random Forest (RF)

In [11]:
```
rf_pipeline = Pipeline([('scaling', StandardScaler()),
                        ('pca', PCA(n_components=None)),
                        ('rf', RandomForestClassifier())
                       ])

param_grid = [{'rf__max_depth': [10, 15, 20],
               'rf__n_estimators': [25, 50, 100],
               'rf__class_weight': [None, 'balanced', 'balanced_subsample'],
               'pca__n_components': [None,10,15,20]
              }]

rf_results = GridSearchCV(estimator=rf_pipeline, param_grid=param_grid, scoring=s
rf_results = rf_results.fit(X_train, y_train)
rf_yhat = rf_results.predict(X_test)

rf_results.best_estimator_
```

Out[11]:
```
Pipeline(steps=[('scaling', StandardScaler()), ('pca', PCA(n_components=20)),
                ('rf',
                 RandomForestClassifier(class_weight='balanced_subsample',
                                        max_depth=20))])
```

In [12]:
```
y_testp = rf_results.predict(X_test)
y_testp_rf = rf_results.predict_proba(X_test)


print(f'Validation score: {rf_results.best_score_:.2%}')
print(f'Test score: {rf_results.score(X_test, y_test):.2%}')


from sklearn.metrics import classification_report
print(classification_report(y_test, y_testp))
```

```
Validation score: 96.49%
Test score: 98.13%
              precision    recall  f1-score   support

        -1.0       0.97      0.86      0.91       312
         0.0       0.91      0.68      0.78       253
         1.0       0.86      0.99      0.92       683

    accuracy                           0.89      1248
   macro avg       0.91      0.84      0.87      1248
weighted avg       0.90      0.89      0.89      1248
```

These are excellent scores. To my knowledge, no target data has been leaked into the training set. I believe this is diractly related to the ticker symbols I've chosen to include. Notes:

- The SVM did better with no PCA while the Random Forest best estimator used a 20 componet PCA. This is probably because of model methods. The RF is constantly splitting data, limiting the data to several components and a tree depth of 20 mostlikely made the weak estimatator forest stronger a whole. Also this RF is uses more data than the previosly pilot tested version in the ChooseModels file, where the RF best estimator use a PCA of 15 and max depth of 15 here both are 20.
- As expected the KNN model is the best estimator over all with a 99% score. What is not expected is that the neighboring range is set to 4 whereas in the pilot test it was set to 1. This means that the large dataset is better understood when grouping by 4s with distance.

Voting Classifier Ensemble

In [13]:
```
ems = [('knn', knn_results.best_estimator_),('rf', rf_results.best_estimator_),('
en = VotingClassifier(estimators=ems, weights=None, voting='soft', n_jobs=-1)
en = en.fit(X_train, y_train)
scores = cross_val_score(estimator=en, X=X_train, y=y_train, cv=10, scoring='roc_
print(f'ROC AUC OVO {scores.mean():.2f} (+/- {scores.std():.2f}) [Ensemble]')
```

```
ROC AUC OVO 0.99 (+/- 0.01) [Ensemble]
```

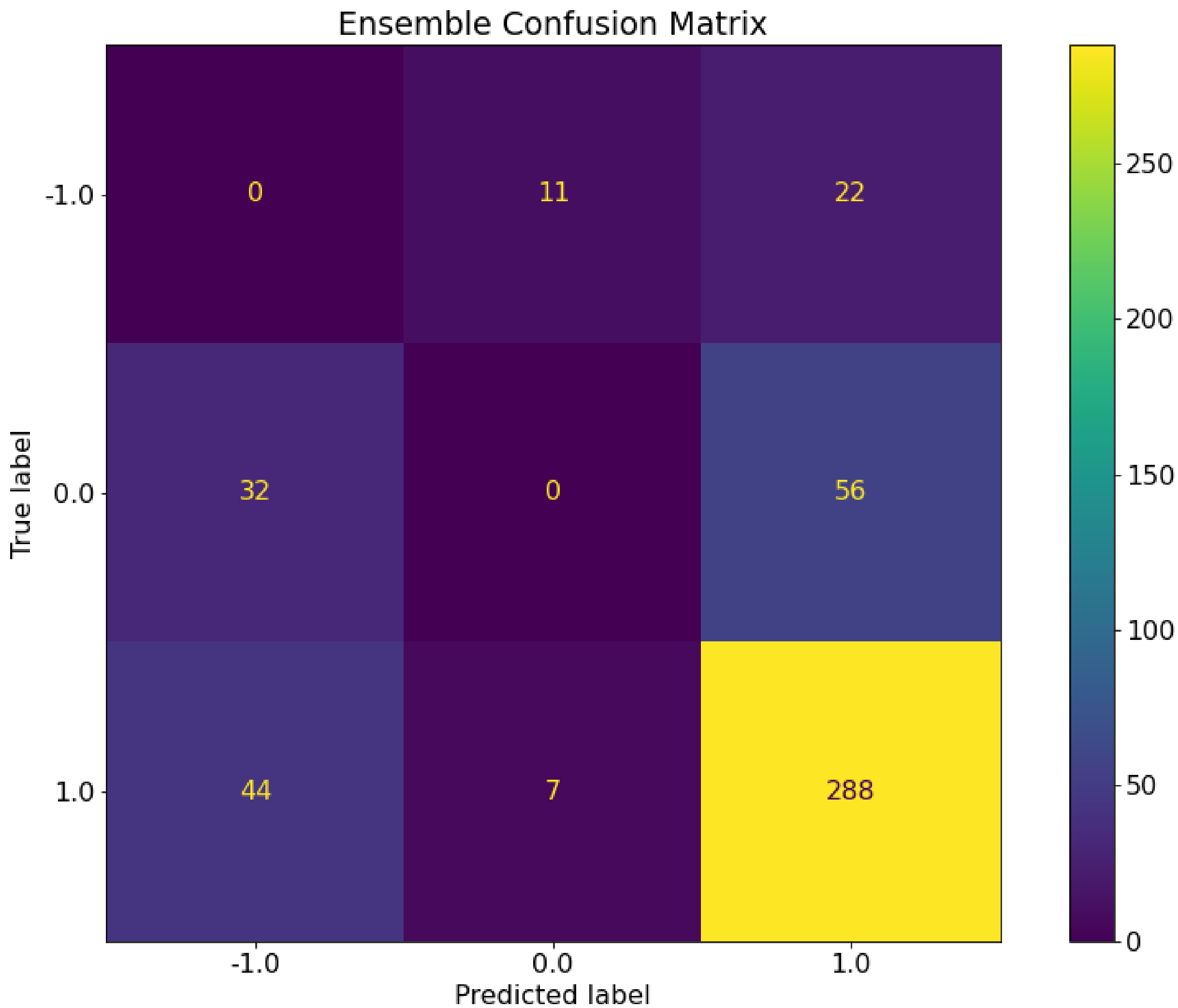
In [14]:
```
y_testp = en.predict(X_test)
y_testp_en = en.predict_proba(X_test)

print(f'Test score: {en.score(X_test, y_test):.2%}')

from sklearn.metrics import classification_report
print(classification_report(y_test, y_testp))
```

```
Test score: 96.15%
              precision    recall  f1-score   support

        -1.0       0.97      0.96      0.96       312
         0.0       0.91      0.90      0.90       253
         1.0       0.98      0.99      0.98       683

    accuracy                           0.96      1248
   macro avg       0.95      0.95      0.95      1248
weighted avg       0.96      0.96      0.96      1248
```

In [15]:
```
ytestp = en.predict(Xtest_ft)
ytestp_en = en.predict_proba(Xtest_ft)

print(f'Test score: {en.score(Xtest_ft, ytest_ft):.2%}')

from sklearn.metrics import classification_report
print(classification_report(ytest_ft, ytestp))
```

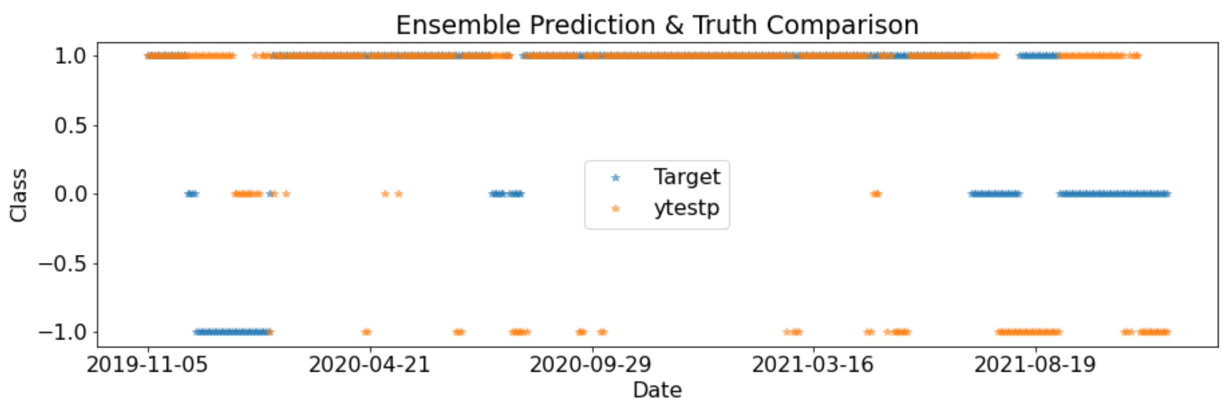
```
Test score: 62.61%
              precision    recall  f1-score   support

        -1.0       0.00      0.00      0.00        33
         0.0       0.00      0.00      0.00        88
         1.0       0.79      0.85      0.82       339

    accuracy                           0.63       460
   macro avg       0.26      0.28      0.27       460
weighted avg       0.58      0.63      0.60       460
```

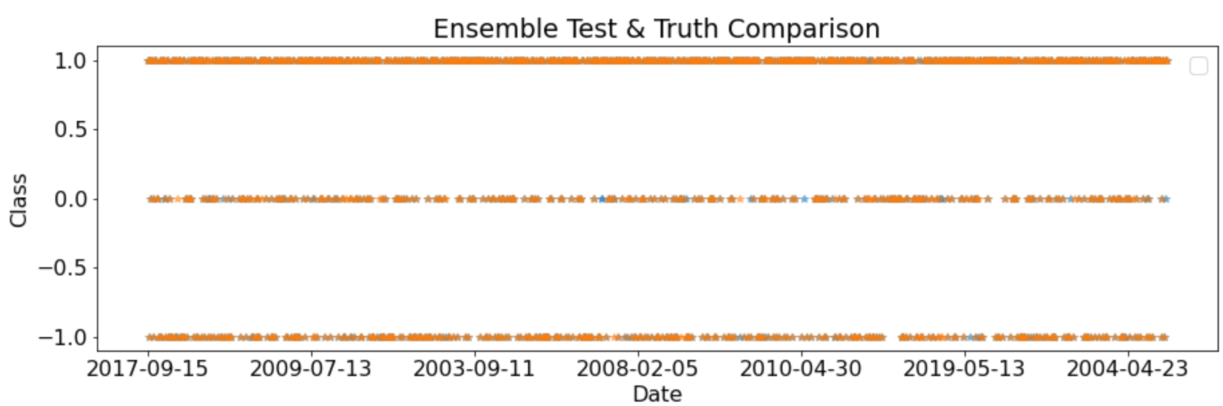
In [100]:
```
#Get the confusion matrix
cf_matrix = confusion_matrix(ytest_ft, ytestp)

fig, ax = plt.subplots(figsize=(15,10))
# ax.subtitle("Best Estimator Confusion Matrix")
disp = ConfusionMatrixDisplay(confusion_matrix=cf_matrix,
                              display_labels=svm_results.best_estimator_.named_st
disp.plot(ax=ax)
ax.set_title("Ensemble Confusion Matrix")
fig.savefig(r"figures\EnsembleConfusionMatrix.png", dpi=600)
plt.show()
```



Seems pretty good at predicting that the market will go up.

In [109]:
```
# Xtrain, Xtest, ytrain, ytest
X_train, X_test, y_train, y_test = create_splits(train_and_test[0], train_and_tes

yTEST = train_and_test[3]
yTEST = pd.concat([yTEST, pd.Series(ytestp, name="ytestp", index=yTEST.index)], a
yTRAIN = pd.concat([y_test, pd.Series(y_testp, name="y_testp", index=y_test.index
fig, (ax1, ax2) = plt.subplots(nrows=2, ncols=1, figsize=(15,10))
yTEST.plot(ax=ax1, style="*", alpha=.5, label="Test Data", fontsize=16)
yTRAIN.plot(ax=ax2, style="*", alpha=.5, label="Training Test Data", fontsize=16)
ax1.legend()
ax2.legend("")
ax1.set_title("Ensemble Prediction & Truth Comparison")
ax2.set_title("Ensemble Test & Truth Comparison")
ax1.set_ylabel("Class")
ax2.set_ylabel("Class")
plt.subplots_adjust(hspace=0.4)
fig.savefig(r"figures\EnsemblePredictionComparison.png", dpi=600)
```





Next Steps!!!

- Needs more tuning...
- Needs another thorough look through...
- Conversion into something deployable

- Train for 14-Day and 7-Day forecasts