In [1]:
```
# Bagging and Boosting
# Example of using bagging and boosting regressors for supervised learning when the target variable is "bounded" by fl
# and ceiling values. By design, tree-based models don't extrapolate outside the target variable range from the traini
# data set; however in this example we demonstrate it is possible for boosting algorithms to produce models that make
# predictions outside the range observed in the data. We'll also look at a few options for mitigating these prediction
# errors, such as transforming the target variable to restrict it to a positive number when making predictions. The ex
# data set has hourly power output from a wind farm (i.e. the target variable) with forecasted weather variables as fe
import sys
import time
import pandas as pd
import numpy as np
import sqlalchemy
import sklearn
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor, HistGradientBoostingRegressor
from sklearn.metrics import mean_squared_error
import xgboost
from xgboost import XGBRFRegressor, XGBRegressor
import plotnine
plotnine.options.figure_size = (9,4.5)
from plotnine import ggplot, aes, geom_histogram, geom_point, geom_smooth, labs, theme_bw, geom_vline
import warnings
warnings.filterwarnings("ignore")
```

In [2]:
```
# Library Versions
print(f"Python {sys.version.split()[0]}")
print(f"NumPy {np.__version__}")
print(f"SQL Alchemy {sqlalchemy.__version__}")
print(f"Pandas {pd.__version__}")
print(f"plotnine {plotnine.__version__}")
print(f"SciKit-Learn {sklearn.__version__}")
print(f"XG Boost {xgboost.__version__}")
```

```
Python 3.10.5
NumPy 1.23.2
SQL Alchemy 1.4.40
Pandas 1.4.3
plotnine 0.10.1
SciKit-Learn 1.1.2
XG Boost 1.7.1
```

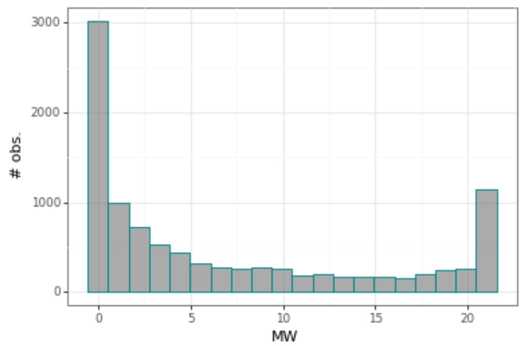
In [3]:
```
# Get Data Frame
sqlquery = """
SELECT TOP (10000) *
FROM [wind].[GetTrainData]
WHERE [Wind] = 'BBWF'
ORDER BY NEWID();
"""
constr = "mssql+pyodbc://RECKONDEV/DataScience?driver=ODBC+Driver+17+for+SQL+Server&TRUSTED_CONNECTION=Yes"
dbcon = sqlalchemy.create_engine(constr)
df = pd.read_sql_query(sql = sqlquery, con = dbcon, parse_dates = ["initTimeUTC","validTimeUTC"])
df.describe()
```

Out[3]:

	mod00z	mod06z	mod12z	mod18z	modGFS	modNAM	yMW	yMWlogit	forecastHour	t2m	...	
count	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	...	1000
mean	0.340600	0.163000	0.336000	0.160400	0.362800	0.637200	6.845920	-1.964781	43.807900	9.342424	...	63
std	0.473935	0.369384	0.472362	0.366995	0.480832	0.480832	7.628919	3.510384	25.977072	12.175565	...	87
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	-6.907000	0.000000	-24.549999	...	
25%	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.200000	-4.659000	21.750000	-0.370000	...	11
50%	0.000000	0.000000	0.000000	0.000000	0.000000	1.000000	3.200000	-1.733000	43.000000	7.515000	...	30
75%	1.000000	0.000000	1.000000	0.000000	1.000000	1.000000	12.800000	0.409000	66.000000	18.719999	...	71
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	21.000000	4.248000	96.000000	38.709999	...	622

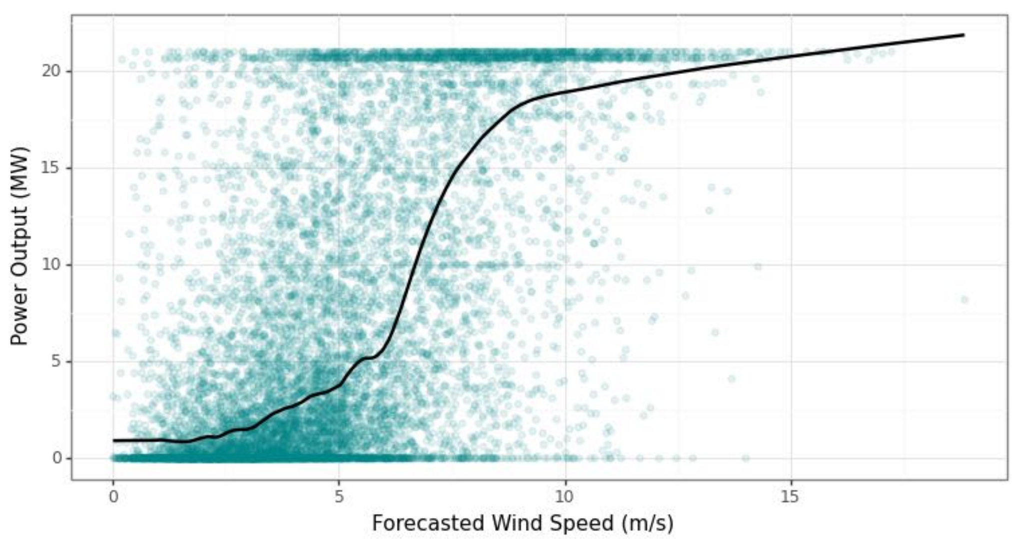
8 rows × 26 columns

In [4]:
```
# Histogram of Target Variable
# Distribution is right skewed, with many values equal to or close to 0
p = (
    ggplot(df, aes(x = "yMW"))
    + geom_histogram(color = "#008789", alpha = 0.5, bins = 20)
    + labs(x = "MW", y = "# obs.")
    + theme_bw()
)
p
```



Out[4]: `<ggplot: (191587551602)>`

In [5]:
```
# Forecast Wind Speed x Power Generation
p = (
    ggplot(df, aes(x = "ws", y = "yMW"))
    + geom_point(color = "#008789", alpha = 0.1)
    + geom_smooth(se = False, method = "lowess", span = 0.1)
    + labs(x = "Forecasted Wind Speed (m/s)", y = "Power Output (MW)")
    + theme_bw()
)
p
```



Out[5]: `<ggplot: (191588109544)>`

In [6]:
```
# Get Maximum Target Value
mw = df.yMW.max()
print(f"Maximum MW = {mw}")
```

```
Maximum MW = 21.0
```

In [7]:
```
# X and y data partitions for model training
# Features (X) are forecasting weather variables like temperature, wind speed, direction
# Target (y) is the generation output from a wind farm
# Each row is an hour, indexed by Date/Time column
xvars = ["forecastHour","t2d","t2m","u10","v10","ws","wdsin","wdcos","pblh","refl","hodsin","hodcos","doysin","doycos"
Xdf = df.loc[:,xvars]
ydf = np.ravel(df.loc[:,["yMW"]]) / mw
print(f"X {Xdf.shape}")
print(f"y {ydf.shape}")
```

```
X (10000, 14)
y (10000,)
```

In [8]:
```
# Training/testing partition
# Note this is technically a time series data set, so for proper parameter tuning and model evaluation we would use
# TimeSeriesSplit instead of train_test_split, but we'll use a simple partition for demonstration purposes.
Xdftrain, Xdftest, ydftrain, ydftest = train_test_split(Xdf, ydf, test_size = 0.2)
print(f"Training Features {Xdftrain.shape}")
print(f"Testing Features {Xdftest.shape}")
print(f"Training Target {ydftrain.shape}")
print(f"Testing Target {ydftest.shape}")
```

```
Training Features (8000, 14)
Testing Features (2000, 14)
Training Target (8000,)
Testing Target (2000,)
```

In [9]:
```
# Print summary stats of the target variable of the training partition
print(f"Minimum = {ydftrain.min():.3}")
print(f"Maximum = {ydftrain.max():.3}")
print(f"   Mean = {ydftrain.mean():.3}")
print(f"Std Dev = {ydftrain.std():.3}")
```

```
Minimum = 0.0
Maximum = 1.0
   Mean = 0.326
Std Dev = 0.363
```

In [10]:
```
# Make a list of maximum depth values, these are used for the bagging and boosting algorithms
# Also, we'll hold the number of trees/iterations to 500 for all the examples
mdlist = [1,2,4,8,16,32]
ntrees = 500
print(f"Max Depths: {mdlist}")
print(f"Trees: {ntrees}")
```

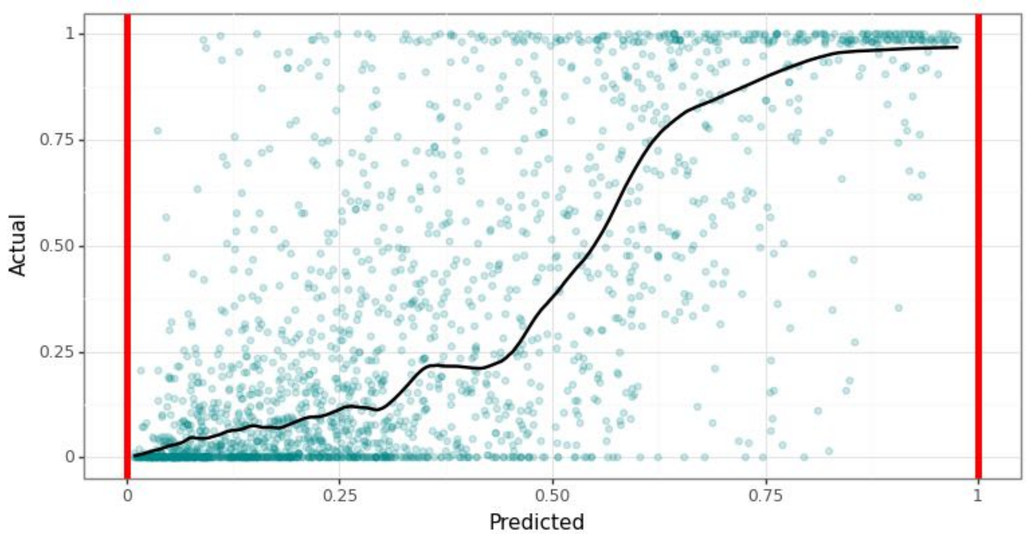
```
Max Depths: [1, 2, 4, 8, 16, 32]
Trees: 500

Trees: 500
```

In [11]:
```
# Fancy Print Function
def funprint(mxdp, prmin, prmax, prer, dur):
    mn = f"{prmin:.2f}"
    mx = f"{prmax:.2f}"
    er = f"{prer:.2f}"
    tm = f"{dur:.2f}"
    print(f"| {mxdp:5d} | {mn:>7} | {mx:>7} | {er:>7} | {tm:>8} |")
```

In [12]:
```
# Random Forest Regressor in Sci-Kit Learn
# https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestRegressor.html
# Other criterion: squared_error, absolute_error, freidman_mse, poisson
print("Random Forest Regressor (Sci-Kit Learn)")
print("--------------------------------------------------")
print("| depth | minimum | maximum |   rmse   | duration |")
print("--------------------------------------------------")
for md in mdlist:
    t1 = time.perf_counter()
    mod = RandomForestRegressor(
        criterion = "friedman_mse",
        max_depth = md,
        n_estimators = ntrees
    ).fit(Xdftrain, ydftrain)
    t2 = time.perf_counter()
    pred = mod.predict(Xdftest)
    rmse = np.sqrt(mean_squared_error(ydftest, pred))
    funprint(md, pred.min(), pred.max(), rmse, t2-t1)
print("--------------------------------------------------")
dfplt = pd.DataFrame({"yMW": ydftest, "xMW": mod.predict(Xdftest)})
p = (
    ggplot(dfplt, aes(x = "xMW", y = "yMW"))
    + geom_point(alpha = 0.2, color = "#008789")
    + geom_smooth(method = "lowess", span = 0.1)
    + labs(x = "Predicted", y = "Actual")
    + geom_vline(xintercept = [ydftrain.min(), ydftrain.max()], color = ["red","red"], size = [2,2])
    + theme_bw()
)
p
```

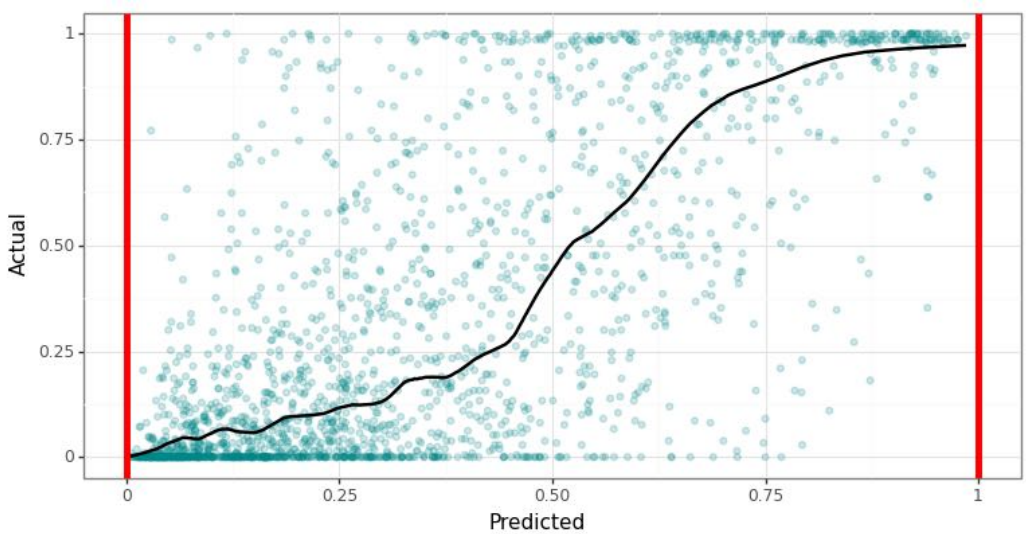
```
Random Forest Regressor (Sci-Kit Learn)
--------------------------------------------------
| depth | minimum | maximum |   rmse   | duration |
--------------------------------------------------
|     1 |    0.21 |    0.65 |    0.30 |     2.09 |
|     2 |    0.13 |    0.75 |    0.29 |     3.59 |
|     4 |    0.09 |    0.88 |    0.27 |     6.62 |
|     8 |    0.05 |    0.94 |    0.26 |    12.70 |
|    16 |    0.01 |    0.97 |    0.25 |    25.29 |
|    32 |    0.01 |    0.98 |    0.25 |    29.24 |
--------------------------------------------------
```



Out[12]: `<ggplot: (191587830214)>`

In [13]:
```
# Random Forest Regressor in XGBoost
# https://xgboost.readthedocs.io/en/stable/tutorials/rf.html
# https://xgboost.readthedocs.io/en/latest/parameter.html
# Other objectives = reg:squarederror, reg:squaredlogerror, reg:logistic, reg:pseudohubererror, count:poisson, reg:gam
print("XGB RF Regressor")
print("--------------------------------------------------")
print("| depth | minimum | maximum |   rmse   | duration |")
print("--------------------------------------------------")
for md in mdlist:
    t1 = time.perf_counter()
    mod = XGBRFRegressor(
        objective = "reg:squarederror",
        max_depth = md,
        n_estimators = ntrees
    ).fit(Xdftrain, ydftrain)
    t2 = time.perf_counter()
    pred = mod.predict(Xdftest)
    rmse = np.sqrt(mean_squared_error(ydftest, pred))
    funprint(md, pred.min(), pred.max(), rmse, t2-t1)
print("--------------------------------------------------")
dfplt = pd.DataFrame({"yMW": ydftest, "xMW": mod.predict(Xdftest)})
p = (
    ggplot(dfplt, aes(x = "xMW", y = "yMW"))
    + geom_point(alpha = 0.2, color = "#008789")
    + geom_smooth(method = "lowess", span = 0.1)
    + labs(x = "Predicted", y = "Actual")
    + geom_vline(xintercept = [ydftrain.min(), ydftrain.max()], color = ["red","red"], size = [2,2])
    + theme_bw()
)
p
```

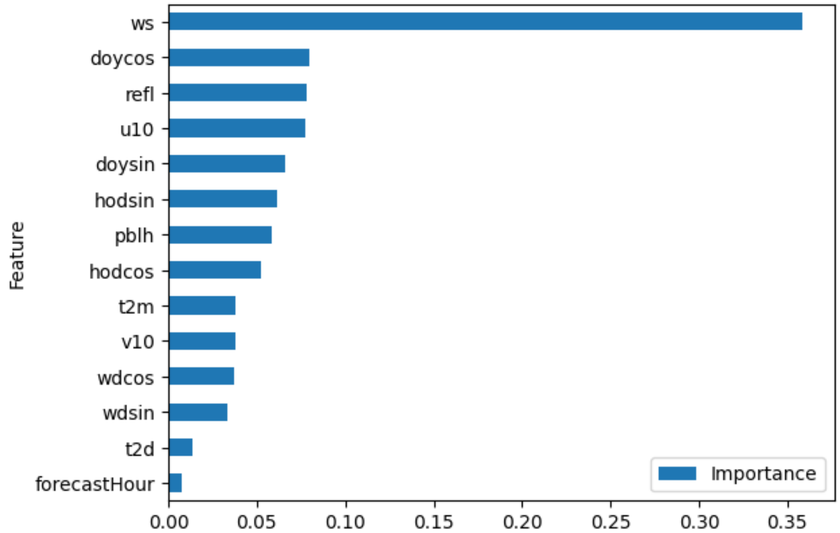
```
XGB RF Regressor
--------------------------------------------------
| depth | minimum | maximum |   rmse   | duration |
--------------------------------------------------
|     1 |    0.21 |    0.65 |    0.30 |     0.79 |
|     2 |    0.15 |    0.76 |    0.29 |     0.53 |
|     4 |    0.09 |    0.87 |    0.27 |     0.92 |
|     8 |    0.05 |    0.94 |    0.26 |     2.13 |
|    16 |    0.01 |    0.98 |    0.25 |    10.51 |
|    32 |    0.00 |    0.99 |    0.25 |    19.22 |
--------------------------------------------------
```



Out[13]: <ggplot: (191587836268)>

In [14]:
```
# RF Feature Importance
dffi = pd.DataFrame({"Feature": xvars, "Importance": mod.feature_importances_}).set_index("Feature").sort_values("Impo
dffi.plot(kind = "barh")
```

Out[14]: <AxesSubplot:ylabel='Feature'>

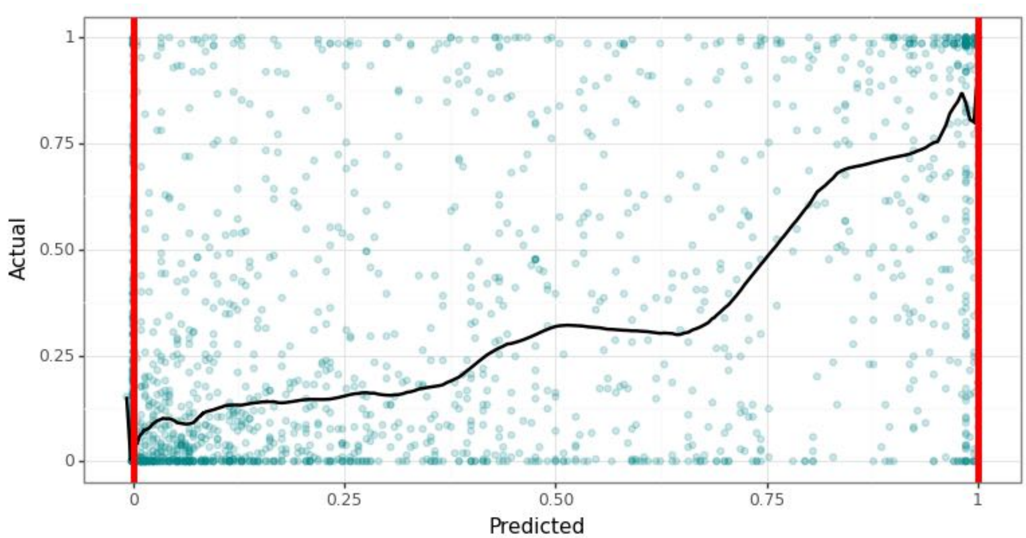


In [15]:
```
# Boosting Algorithms
# We'll try max depth as well as learning rate for boosting algos
lrlist = [0.01,0.1,1.0]
print(f"Learning Rates: {lrlist}")
```

```
Learning Rates: [0.01, 0.1, 1.0]
```

In [16]:
```
# Gradient Boosting Regressor
# https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.GradientBoostingRegressor.html
# Other loss options: squared_error, absolute_error, huber, quantile (requires alpha)
print("Gradient Boosting Regressor w/ Squared Error Loss")
print("--------------------------------------------------")
print("| depth | minimum | maximum |   rmse   | duration |")
print("--------------------------------------------------")
for lr in lrlist:
    print(f"Learning Rate = {lr}")
    for md in mdlist:
        t1 = time.perf_counter()
        mod = GradientBoostingRegressor(
            loss = "squared_error",
            max_depth = md,
            learning_rate = lr,
            n_estimators = ntrees
        ).fit(Xdftrain, ydftrain)
        t2 = time.perf_counter()
        pred = mod.predict(Xdftest)
        rmse = np.sqrt(mean_squared_error(ydftest, pred))
        funprint(md, pred.min(), pred.max(), rmse, t2-t1)
print("--------------------------------------------------")
dfplt = pd.DataFrame({"yMW": ydftest, "xMW": mod.predict(Xdftest)})
p = (
    ggplot(dfplt, aes(x = "xMW", y = "yMW"))
    + geom_point(alpha = 0.2, color = "#008789")
    + geom_smooth(method = "lowess", span = 0.1)
    + labs(x = "Predicted", y = "Actual")
    + geom_vline(xintercept = [ydftrain.min(), ydftrain.max()], color = ["red","red"], size = [2,2])
    + theme_bw()
)
p
```

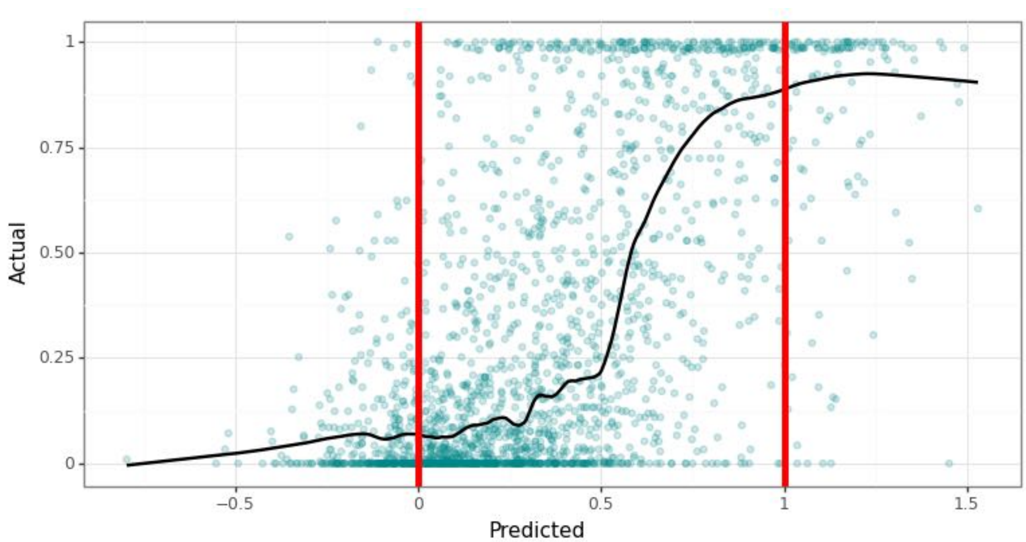
```
Gradient Boosting Regressor w/ Squared Error Loss
--------------------------------------------------
| depth | minimum | maximum |   rmse   | duration |
--------------------------------------------------
Learning Rate = 0.01
|     1 |    0.06 |    0.78 |    0.28 |     3.16 |
|     2 |    0.02 |    0.91 |    0.27 |     6.07 |
|     4 |    0.02 |    0.98 |    0.26 |    11.46 |
|     8 |   -0.00 |    0.99 |    0.25 |    22.42 |
|    16 |   -0.00 |    1.01 |    0.29 |    40.77 |
|    32 |    0.00 |    1.00 |    0.34 |    50.30 |
Learning Rate = 0.1
|     1 |   -0.07 |    1.03 |    0.27 |     2.99 |
|     2 |   -0.09 |    1.08 |    0.26 |     6.04 |
|     4 |   -0.19 |    1.26 |    0.25 |    11.84 |
|     8 |   -0.07 |    1.26 |    0.25 |    23.09 |
|    16 |   -0.03 |    1.02 |    0.29 |    44.47 |
|    32 |   -0.00 |    1.00 |    0.34 |    15.96 |
Learning Rate = 1.0
|     1 |   -0.15 |    1.10 |    0.27 |     3.02 |
|     2 |   -0.54 |    1.54 |    0.29 |     5.85 |
|     4 |   -0.66 |    1.73 |    0.33 |    11.80 |
|     8 |   -1.23 |    2.11 |    0.36 |    20.78 |
|    16 |   -0.49 |    1.84 |    0.36 |     3.38 |
|    32 |   -0.01 |    1.00 |    0.35 |     0.29 |
--------------------------------------------------
```



Out[16]: <ggplot: (191588223871)>

In [17]:
```
# Hist Gradient Boosting Regressor
# https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.HistGradientBoostingRegressor.html
# Other loss options: squared_error, absolute_error, poisson, quantile (requires quantile)
print("Hist Gradient Boosting Regressor w/ Squared Error Loss")
print("--------------------------------------------------")
print("| depth | minimum | maximum |   rmse   | duration |")
print("--------------------------------------------------")
for lr in lrlist:
    print(f"Learning Rate = {lr}")
    for md in mdlist:
        t1 = time.perf_counter()
        mod = HistGradientBoostingRegressor(
            loss = "squared_error",
            max_depth = md,
            learning_rate = lr,
            max_iter = ntrees
        ).fit(Xdftrain, ydftrain)
        t2 = time.perf_counter()
        pred = mod.predict(Xdftest)
        rmse = np.sqrt(mean_squared_error(ydftest, pred))
        funprint(md, pred.min(), pred.max(), rmse, t2-t1)
print("--------------------------------------------------")
dfplt = pd.DataFrame({"yMW": ydftest, "xMW": mod.predict(Xdftest)})
p = (
    ggplot(dfplt, aes(x = "xMW", y = "yMW"))
    + geom_point(alpha = 0.2, color = "#008789")
    + geom_smooth(method = "lowess", span = 0.1)
    + labs(x = "Predicted", y = "Actual")
    + geom_vline(xintercept = [ydftrain.min(), ydftrain.max()], color = ["red","red"], size = [2,2])
    + theme_bw()
)
p
```

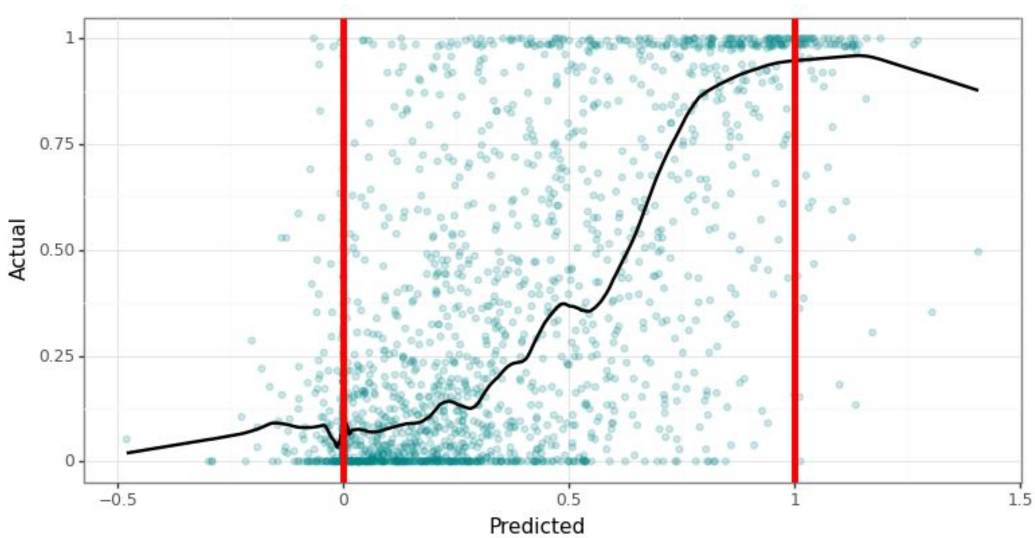
```
Hist Gradient Boosting Regressor w/ Squared Error Loss
--------------------------------------------------
| depth | minimum | maximum |   rmse   | duration |
--------------------------------------------------
Learning Rate = 0.01
|     1 |    0.06 |    0.78 |    0.28 |     0.41 |
|     2 |    0.03 |    0.91 |    0.27 |     0.47 |
|     4 |   -0.00 |    0.98 |    0.26 |     1.08 |
|     8 |    0.02 |    0.99 |    0.25 |     2.62 |
|    16 |    0.01 |    0.99 |    0.25 |     2.86 |
|    32 |    0.01 |    0.99 |    0.25 |     2.77 |
Learning Rate = 0.1
|     1 |   -0.07 |    1.02 |    0.27 |     0.36 |
|     2 |   -0.09 |    1.16 |    0.26 |     0.47 |
|     4 |   -0.11 |    1.19 |    0.25 |     1.02 |
|     8 |   -0.09 |    1.14 |    0.24 |     2.42 |
|    16 |   -0.12 |    1.14 |    0.25 |     2.45 |
|    32 |   -0.08 |    1.18 |    0.25 |     2.66 |
Learning Rate = 1.0
|     1 |   -0.13 |    1.15 |    0.27 |     0.37 |
|     2 |   -0.34 |    1.40 |    0.27 |     0.50 |
|     4 |   -0.76 |    1.54 |    0.32 |     1.06 |
|     8 |   -0.68 |    1.58 |    0.33 |     2.33 |
|    16 |   -0.80 |    1.53 |    0.32 |     2.52 |
|    32 |   -0.80 |    1.53 |    0.32 |     2.56 |
--------------------------------------------------
```



Out[17]: <ggplot: (191588470331)>

In [18]:
```
# Hist Gradient Boosting Regressor with Quantile Loss
print("Hist Gradient Boosting Regressor w/ Quantile Loss")
print("---------------------------------------------------")
print("| depth | minimum | maximum |   rmse   | duration |")
print("---------------------------------------------------")
for lr in lrlist:
    print(f"Learning Rate = {lr}")
    for md in mdlist:
        t1 = time.perf_counter()
        mod = HistGradientBoostingRegressor(
            max_depth = md,
            learning_rate = lr,
            loss = "quantile",
            quantile = 0.5,
            max_iter = ntrees
        ).fit(Xdftrain, ydftrain)
        t2 = time.perf_counter()
        pred = mod.predict(Xdftest)
        rmse = np.sqrt(mean_squared_error(ydftest, pred))
        funprint(md, pred.min(), pred.max(), rmse, t2-t1)
print("---------------------------------------------------")
dfplt = pd.DataFrame({"yMW": ydftest, "xMW": mod.predict(Xdftest)})
p = (
    ggplot(dfplt, aes(x = "xMW", y = "yMW"))
    + geom_point(alpha = 0.2, color = "#008789")
    + geom_smooth(method = "lowess", span = 0.1)
    + labs(x = "Predicted", y = "Actual")
    + geom_vline(xintercept = [ydftrain.min(), ydftrain.max()], color = ["red","red"], size = [2,2])
    + theme_bw()
)
p
```

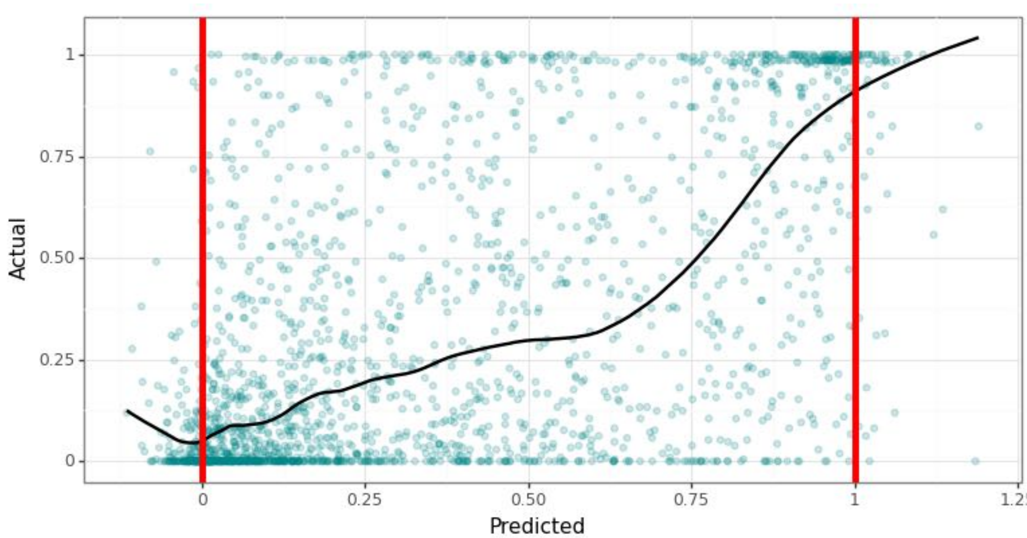
```
Hist Gradient Boosting Regressor w/ Quantile Loss
--------------------------------------------------
| depth | minimum | maximum |   rmse   | duration |
--------------------------------------------------
Learning Rate = 0.01
|     1 |   -0.01 |    0.94 |    0.29 |     0.69 |
|     2 |   -0.01 |    1.01 |    0.29 |     0.90 |
|     4 |   -0.01 |    1.04 |    0.27 |     2.34 |
|     8 |   -0.05 |    1.00 |    0.27 |     5.09 |
|    16 |   -0.07 |    1.01 |    0.27 |     5.02 |
|    32 |   -0.07 |    1.01 |    0.27 |     4.99 |
Learning Rate = 0.1
|     1 |   -0.05 |    1.05 |    0.29 |     0.64 |
|     2 |   -0.04 |    1.12 |    0.28 |     0.91 |
|     4 |   -0.08 |    1.22 |    0.26 |     1.95 |
|     8 |   -0.12 |    1.11 |    0.26 |     4.45 |
|    16 |   -0.16 |    1.12 |    0.26 |     4.64 |
|    32 |   -0.07 |    1.14 |    0.26 |     4.61 |
Learning Rate = 1.0
|     1 |    0.00 |    0.76 |    0.30 |     0.66 |
|     2 |   -0.14 |    1.18 |    0.28 |     0.90 |
|     4 |   -0.37 |    1.56 |    0.28 |     2.15 |
|     8 |   -0.51 |    1.40 |    0.28 |     4.57 |
|    16 |   -0.48 |    1.41 |    0.29 |     4.98 |
|    32 |   -0.48 |    1.41 |    0.29 |     4.63 |
--------------------------------------------------
```



```
Out[18]: <ggplot: (191588060740)>
```

In [19]:
```
# XGB Regressor
# https://xgboost.readthedocs.io/en/latest/python/python_api.html
print("XGB Regressor w/ Squared Error Objective")
print("--------------------------------------------------")
print("| depth | minimum | maximum |   rmse   | duration |")
print("--------------------------------------------------")
for lr in lrlist:
    print(f"Learning Rate = {lr}")
    for md in mdlist:
        t1 = time.perf_counter()
        mod = XGBRegressor(
            objective = "reg:squarederror",
            tree_method = "hist",
            max_depth = md,
            learning_rate = lr,
            n_estimators = ntrees
        ).fit(Xdftrain, ydftrain)
        t2 = time.perf_counter()
        pred = mod.predict(Xdftest)
        rmse = np.sqrt(mean_squared_error(ydftest, pred))
        funprint(md, pred.min(), pred.max(), rmse, t2-t1)
print("--------------------------------------------------")
dfplt = pd.DataFrame({"yMW": ydftest, "xMW": mod.predict(Xdftest)})
p = (
    ggplot(dfplt, aes(x = "xMW", y = "yMW"))
    + geom_point(alpha = 0.2, color = "#008789")
    + geom_smooth(method = "lowess", span = 0.2)
    + labs(x = "Predicted", y = "Actual")
    + geom_vline(xintercept = [ydftrain.min(), ydftrain.max()], color = ["red","red"], size = [2,2])
    + theme_bw()
)
p
```

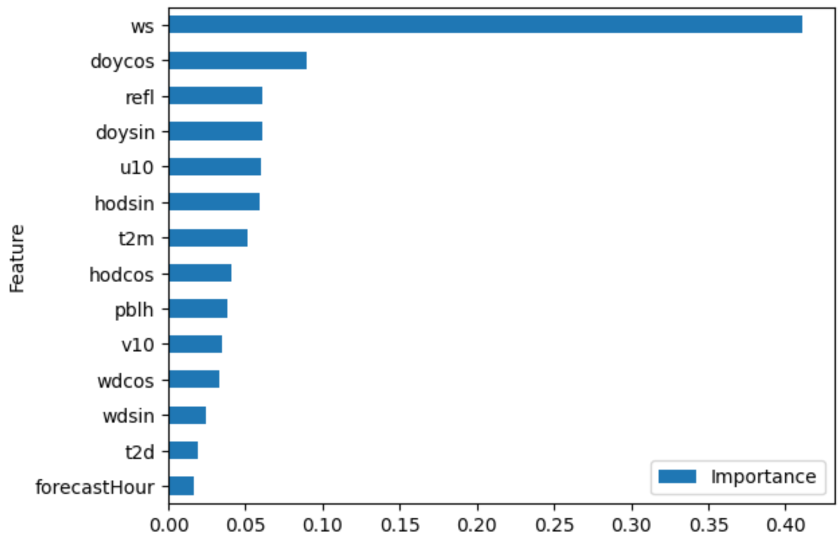
```
XGB Regressor w/ Squared Error Objective
--------------------------------------------------
| depth | minimum | maximum |   rmse   | duration |
--------------------------------------------------
Learning Rate = 0.01
|     1 |    0.07 |    0.78 |    0.28 |     0.20 |
|     2 |    0.03 |    0.91 |    0.27 |     0.21 |
|     4 |    0.01 |    0.98 |    0.26 |     0.33 |
|     8 |   -0.01 |    1.02 |    0.25 |     1.25 |
|    16 |   -0.01 |    1.00 |    0.26 |    11.41 |
|    32 |   -0.00 |    1.01 |    0.27 |    17.70 |
Learning Rate = 0.1
|     1 |   -0.07 |    1.02 |    0.27 |     0.18 |
|     2 |   -0.09 |    1.11 |    0.26 |     0.20 |
|     4 |   -0.09 |    1.15 |    0.25 |     0.32 |
|     8 |   -0.07 |    1.09 |    0.25 |     1.08 |
|    16 |   -0.02 |    1.01 |    0.26 |     2.52 |
|    32 |   -0.01 |    1.01 |    0.26 |     3.19 |
Learning Rate = 1.0
|     1 |   -0.13 |    1.13 |    0.27 |     0.15 |
|     2 |   -0.43 |    1.40 |    0.27 |     0.20 |
|     4 |   -0.51 |    1.48 |    0.31 |     0.33 |
|     8 |   -0.44 |    1.49 |    0.32 |     0.42 |
|    16 |   -0.15 |    1.30 |    0.33 |     0.55 |
|    32 |   -0.12 |    1.19 |    0.33 |     0.77 |
--------------------------------------------------
```



Out[19]: <ggplot: (191587884477)>

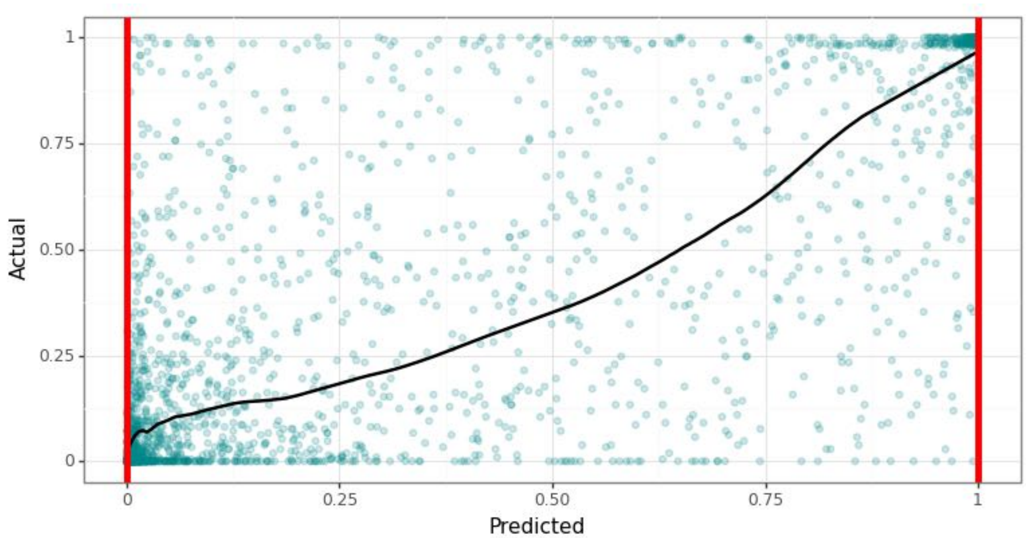
In [20]:
```
# XGB Feature Importance
dffi = pd.DataFrame({"Feature": xvars, "Importance": mod.feature_importances_}).set_index("Feature").sort_values("Impo
dffi.plot(kind = "barh")
```

Out[20]: <AxesSubplot:ylabel='Feature'>



In [21]:
```
# XGB Regressor with Logistic Objective
# Use objective = 'reg:logistic' in XGBRegressor
print("XGB Regressor w/ Logistic Objective")
print("--------------------------------------------------")
print("| depth | minimum | maximum |   rmse   | duration |")
print("--------------------------------------------------")
for lr in lrlist:
    print(f"Learning Rate = {lr}")
    for md in mdlist:
        t1 = time.perf_counter()
        mod = XGBRegressor(
            tree_method = "hist",
            max_depth = md,
            learning_rate = lr,
            objective = "reg:logistic",
            n_estimators = ntrees
        ).fit(Xdftrain, ydftrain)
        t2 = time.perf_counter()
        pred = mod.predict(Xdftest)
        rmse = np.sqrt(mean_squared_error(ydftest, pred))
        funprint(md, pred.min(), pred.max(), rmse, t2-t1)
print("--------------------------------------------------")
dfplt = pd.DataFrame({"yMW": ydftest, "xMW": mod.predict(Xdftest)})
p = (
    ggplot(dfplt, aes(x = "xMW", y = "yMW"))
    + geom_point(alpha = 0.2, color = "#008789")
    + geom_smooth(method = "lowess", span = 0.2)
    + labs(x = "Predicted", y = "Actual")
    + geom_vline(xintercept = [ydftrain.min(), ydftrain.max()], color = ["red","red"], size = [2,2])
    + theme_bw()
)
p
```

```
XGB Regressor w/ Logistic Objective
--------------------------------------------------
| depth | minimum | maximum |   rmse   | duration |
--------------------------------------------------
Learning Rate = 0.01
|     1 |    0.10 |    0.76 |    0.28 |     0.19 |
|     2 |    0.07 |    0.88 |    0.27 |     0.21 |
|     4 |    0.05 |    0.94 |    0.26 |     0.34 |
|     8 |    0.02 |    0.98 |    0.25 |     1.05 |
|    16 |    0.01 |    0.98 |    0.25 |     3.80 |
|    32 |    0.01 |    0.98 |    0.25 |     4.94 |
Learning Rate = 0.1
|     1 |    0.03 |    0.95 |    0.27 |     0.17 |
|     2 |    0.02 |    0.98 |    0.26 |     0.21 |
|     4 |    0.01 |    1.00 |    0.25 |     0.31 |
|     8 |    0.00 |    1.00 |    0.24 |     0.87 |
|    16 |    0.00 |    1.00 |    0.25 |     2.67 |
|    32 |    0.00 |    1.00 |    0.25 |     4.12 |
Learning Rate = 1.0
|     1 |    0.02 |    0.98 |    0.27 |     0.17 |
|     2 |    0.00 |    1.00 |    0.27 |     0.20 |
|     4 |    0.00 |    1.00 |    0.28 |     0.33 |
|     8 |    0.00 |    1.00 |    0.28 |     0.93 |
|    16 |    0.00 |    1.00 |    0.28 |     2.57 |
|    32 |    0.00 |    1.00 |    0.29 |     3.78 |
--------------------------------------------------
```

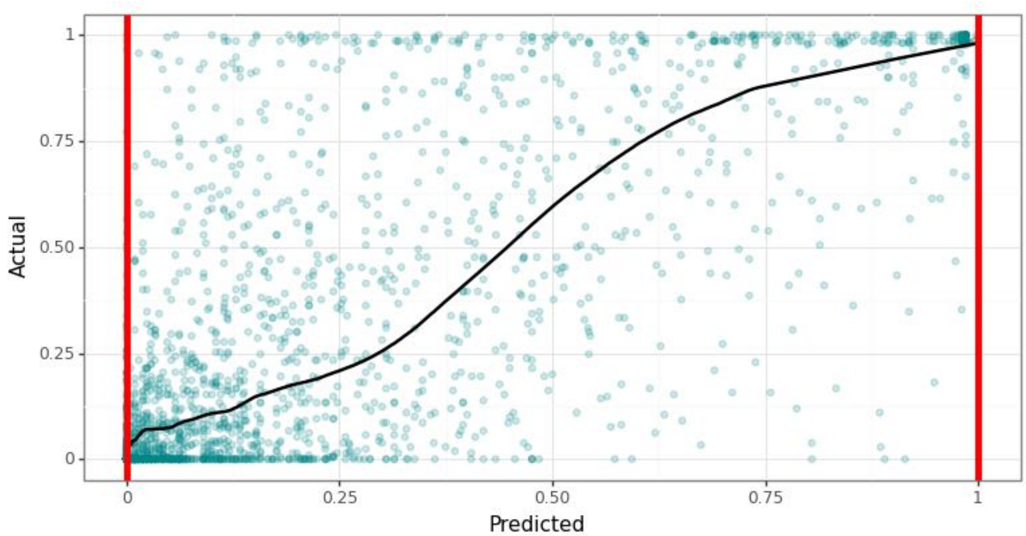


Out[21]: <ggplot: (191626864517)>

In [22]:
```python
# Sci-Kit Learn TransformedTargetRegressor
# build a model pipeline
# (https://scikit-learn.org/stable/modules/generated/sklearn.pipeline.Pipeline.html#sklearn.pipeline.Pipeline)
# with one of the steps using Transformed Target Regressor
# (https://scikit-learn.org/stable/modules/generated/sklearn.compose.TransformedTargetRegressor.html#)
from sklearn.compose import TransformedTargetRegressor
from sklearn.preprocessing import QuantileTransformer
from sklearn.pipeline import make_pipeline
```

In [23]:
```python
# Make Model Pipeline with Transformed Target Regressor
pipe = make_pipeline(
    TransformedTargetRegressor(
        regressor = XGBRegressor(
            tree_method = "hist",
            n_estimators = 500,
            max_depth = 8,
            learning_rate = 0.01
        ),
        transformer = QuantileTransformer(
            output_distribution = "uniform"
        )
    )
).fit(Xdftrain, ydftrain)
pred = pipe.predict(Xdftest)
```

In [24]:
```python
# Plot Pipeline Model Predictions
dfplt = pd.DataFrame({"yMW": ydftest, "xMW": pred})
p = (
    ggplot(dfplt, aes(x = "xMW", y = "yMW"))
    + geom_point(alpha = 0.2, color = "#008789")
    + geom_smooth(method = "lowess", span = 0.2)
    + labs(x = "Predicted", y = "Actual")
    + geom_vline(xintercept = [ydftrain.min(), ydftrain.max()], color = ["red","red"], size = [2,2])
    + theme_bw()
)
p
```



Out[24]: <ggplot: (191626680972)>

In [25]:
```python
# Print Predicted Min/Max Values
print(f"Predicted Min = {pred.min():.1f}")
print(f"Predicted Max = {pred.max():.1f}")
```

```
Predicted Min = 0.0
Predicted Max = 1.0
```