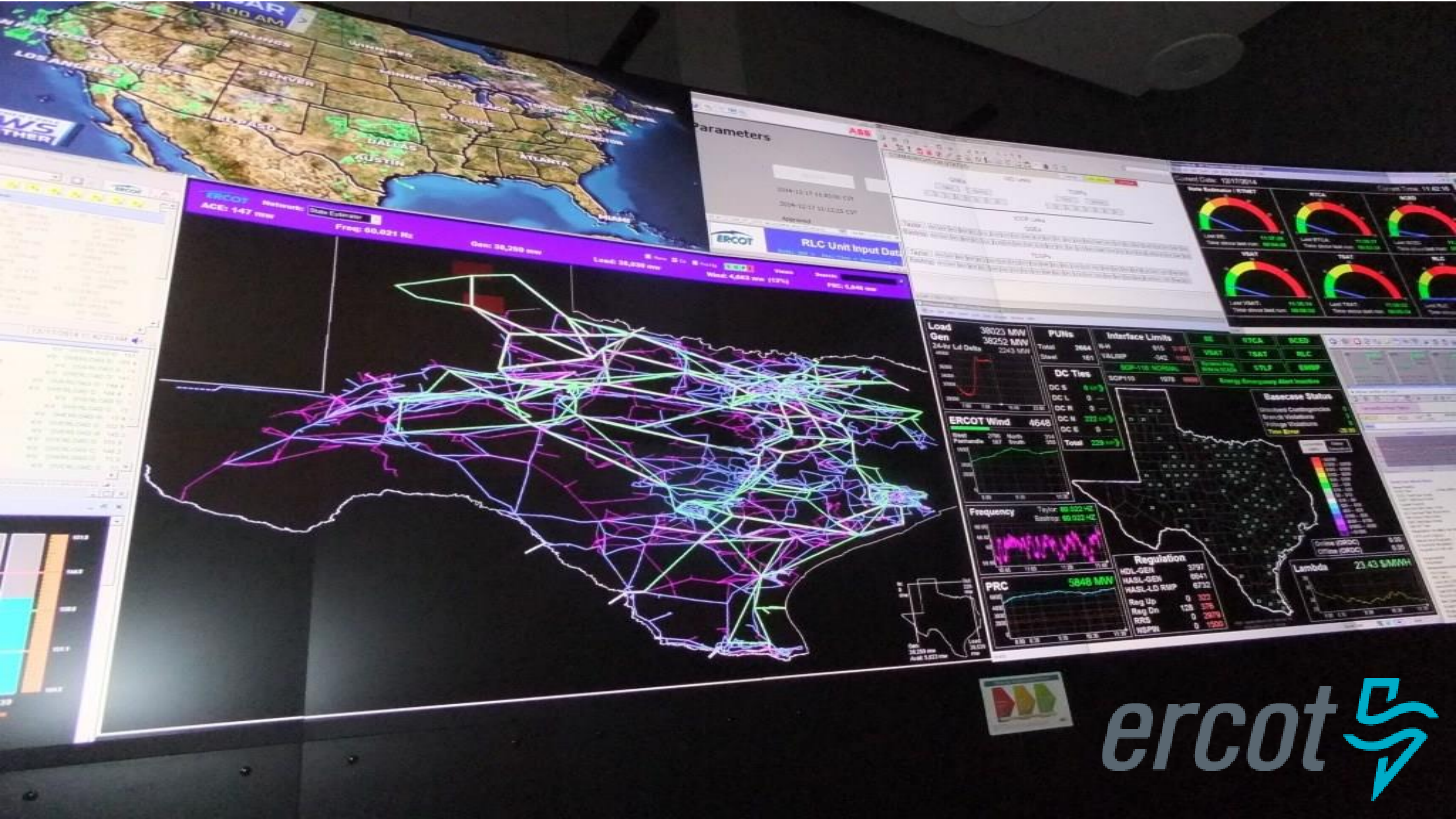
PREDICTING TEXAS ELECTRICITY SPOT PRICES

PAIGE BAILEY // JULY 5TH, 2017



LOS ANGELES
DENVER
CHICAGO
DALLAS
AUSTIN
ATLANTA
MIAMI
Parameters
ABB
ERCOT
RLC Unit Input Dat
Load
Gen
PUNs
Interface Limits
DC Ties
ERCOT Wind
4648
Basecase Status
Frequency
PRC
5848 MW
Regulation
Lambda
23.43 $/MWH
ercot

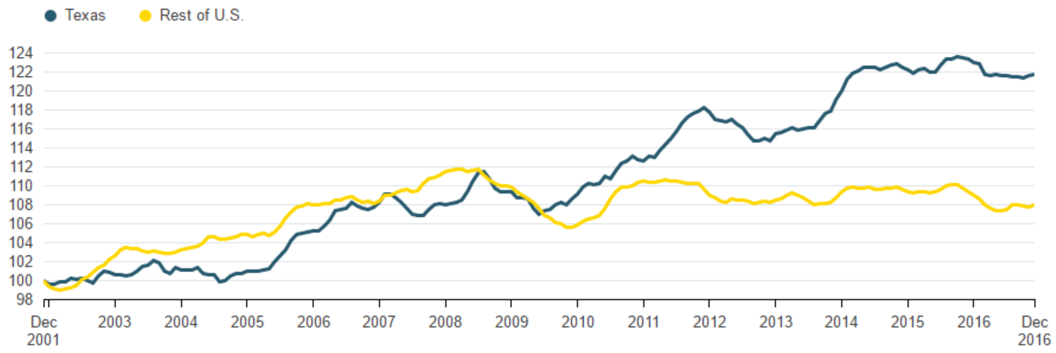
MOTIVATION

BRIEF

ERCOT: Narrow reserves boost real-time prices above $700/MWh

Lone Star State

Texas' electricity demand kept growing after 2008, unlike the U.S. overall



Source: Energy Information Administration

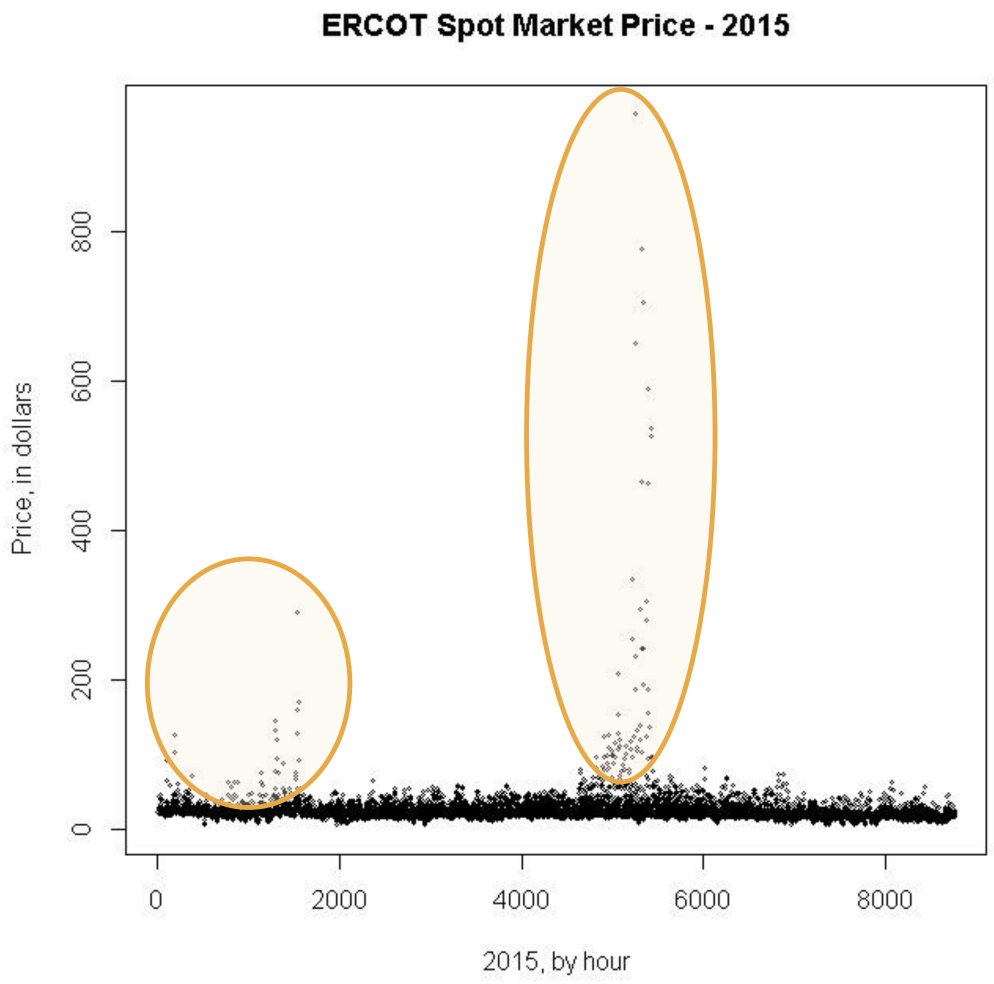
Note: Trailing 12-month retail sales of electricity, indexed to 100 in December 2001.

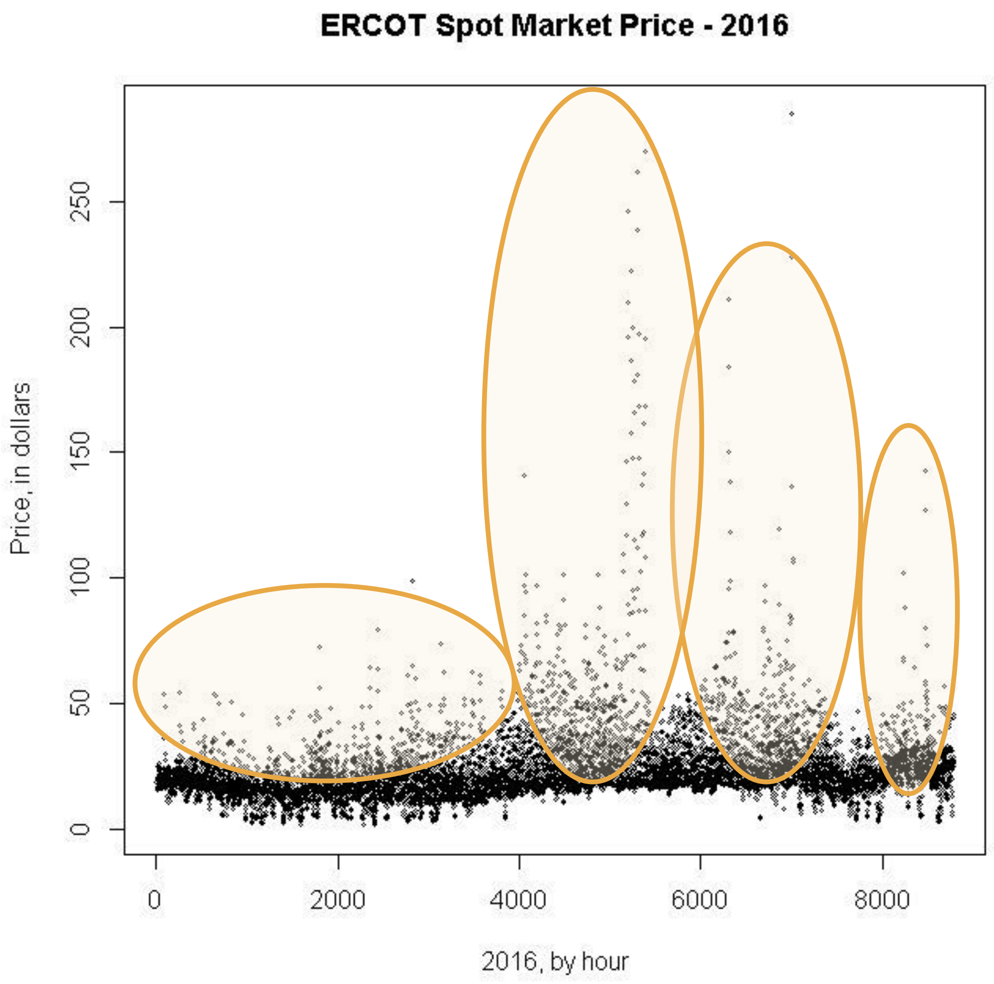
from the Houston Chronicle:

By late afternoon on February 22, 2017, temperatures around [Texas] had climbed into the 90s, and the demand for power surged. **In Houston, where midday wholesale power prices typically hover around $25, the price spiked to $4,000 per megawatt-hour** - a sign that the market was short of supply.

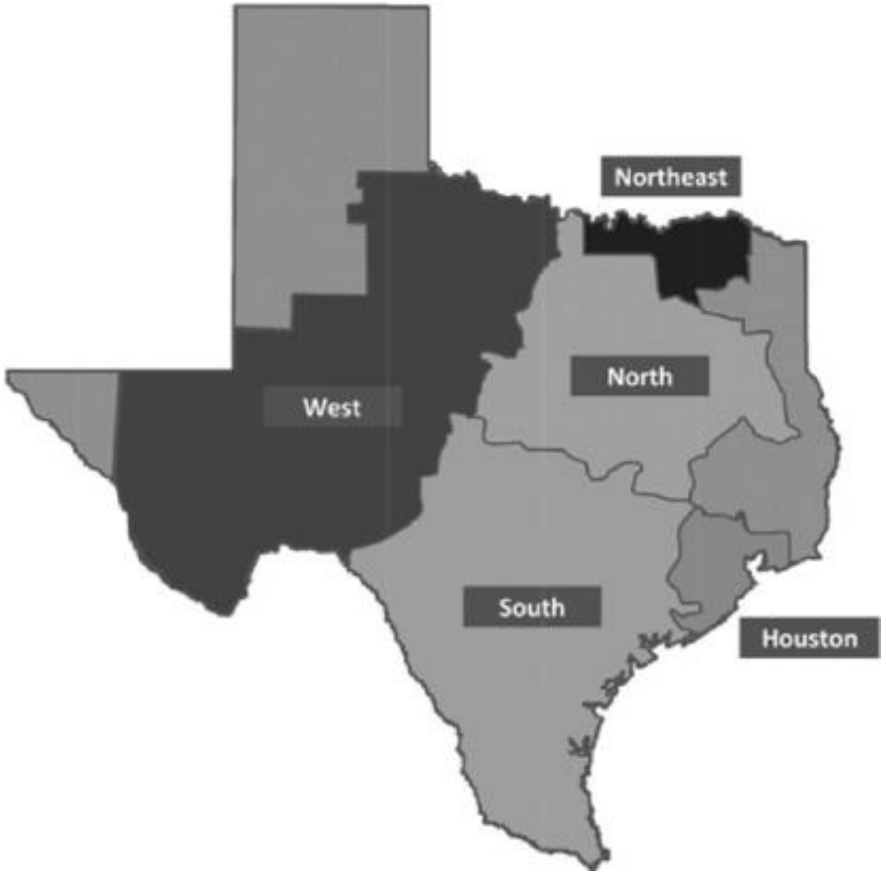
Houston has a capacity problem, and energy demand is only anticipated to increase.

VARIABILITY IN ELECTRICITY PRICES





- How do **weather patterns** in Houston (humidity, precipitation, temperature) impact price of electricity for the Houston hub?
- What other **factors or combination of factors** impact electricity prices in the Houston hub?
- What are the **optimal times** to purchase electricity at the Houston hub? To sell?
- How could you **operationalize the purchase** of electricity for a business, on a short-term and long-term basis?



RESEARCH QUESTIONS

DATA SOURCES

ERCOT

Real-Time Settlement Point Prices Display

*SPP values **include** the 15 Minute Online Reserve Price Adders and the Real-Time Online Reliability Deployment Price Adders.*

Operating Day: 03/03/2017 ▾

Oper Day	Interval Ending	HB_BUSAVG	HB_HOUSTON	HB_HUBAVG	HB_NORTH	HB_SOUTH	HB_WEST	LZ_AEN
03/03/2017	0015	14.64	14.64	14.64	14.64	14.64	14.64	14.64
03/03/2017	0030	14.53	14.53	14.53	14.53	14.53	14.53	14.53
03/03/2017	0045	14.49	14.49	14.49	14.49	14.49	14.49	14.49
03/03/2017	0100	14.33	14.33	14.33	14.33	14.33	14.33	14.33
03/03/2017	0115	14.11	14.11	14.11	14.11	14.11	14.11	14.11
03/03/2017	0130	14.02	14.02	14.02	14.02	14.02	14.02	14.02
03/03/2017	0145	13.96	13.96	13.96	13.96	13.96	13.96	13.96
03/03/2017	0200	14.08	14.08	14.08	14.08	14.08	14.08	14.08
03/03/2017	0215	14.00	14.00	14.00	14.00	14.00	14.00	14.00
03/03/2017	0230	13.90	13.90	13.90	13.90	13.90	13.90	13.90
03/03/2017	0245	14.13	14.13	14.13	14.13	14.13	14.13	14.13
03/03/2017	0300	14.44	14.44	14.44	14.44	14.44	14.44	14.44
03/03/2017	0315	14.35	14.35	14.35	14.35	14.35	14.35	14.35
03/03/2017	0330	14.34	14.34	14.34	14.34	14.34	14.34	14.34
03/03/2017	0345	14.07	14.07	14.07	14.07	14.07	14.07	14.07
03/03/2017	0400	14.07	14.07	14.07	14.07	14.07	14.07	14.07
03/03/2017	0415	14.63	14.63	14.63	14.63	14.63	14.63	14.63
03/03/2017	0430	14.82	14.82	14.82	14.82	14.82	14.82	14.82
03/03/2017	0445	15.01	15.01	15.01	15.01	15.01	15.01	15.01
03/03/2017	0500	15.06	15.06	15.06	15.06	15.06	15.06	15.06
03/03/2017	0515	15.51	15.51	15.51	15.51	15.51	15.51	15.51
03/03/2017	0530	15.72	15.72	15.72	15.72	15.72	15.72	15.72
03/03/2017	0545	16.16	16.16	16.16	16.16	16.16	16.16	16.16
03/03/2017	0600	16.71	16.71	16.71	16.71	16.71	16.71	16.71
03/03/2017	0615	17.73	17.73	17.73	17.73	17.73	17.73	17.73
03/03/2017	0630	18.98	18.98	18.98	18.98	18.98	18.98	18.98
03/03/2017	0645	20.20	20.20	20.20	20.20	20.20	20.20	20.20

MRCC CLI-MATE DATA

Hourly Data Between Two Dates
HOUSTON HOBBY AP (TX)
12918
Lat/Lon/Elev: 29.6381/-95.2819/44 ft

Date	Time	Temp (F)	RH (%)	Dewpt (F)	Wind Spd (mph)	Wind Direction (deg)	Peak Wind Gust(mph)	Atm Press (hPa)	Precip (in)	Wind Chill (F)	Heat Index (F)
2011-01-01	00:00	63	35	35	16	20	M	1009.03	M	NC	NC
2010-01-01	01:00	49	77	42	20	330	24	1024.27	M	NC	NC
2010-01-01	02:00	47	80	41	20	340	29	1024.94	M	40	NC

Time Range: 2010 – present
Sampling Rate: every 15 minutes / hourly
Weather Prediction: darksky (R package)

DATA PREPARATION

- Consistent date/time formats
- Derived column for z-scores
- Derive "class" column based on z-score
  - SELL: z-score greater than or equal to 1
  - HOLD: z-score between -1 and 1
  - BUY: z-score greater than or equal to -1
- Average monthly pricing
- Determine appropriate segmentation for weather
  - By month? By season?
  - By time of day, or hour?
  - Some combination?

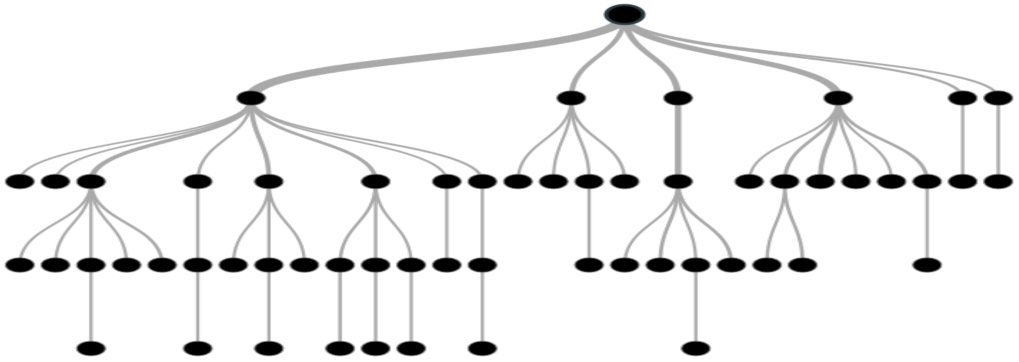
DATA ANALYSIS

Data Acquisition

- Obtain developer credentials for **DarkSky**
- Install **darksky** package in R
- Download data from **ERCOT website** (2010-2017)
- Download data from **MRCC website** (2010-2017)

ERCOT: approximately 75,000 observations per month, over a span of 77 months (~5.775MM)

MRCC: hourly observations, since 2010 (54,191)



Algorithms to Test

- Both numeric and categorical features
- Focus on usability for end user, as well as confidence for ability to predict
- Algorithms Tested
  - Decision Tree (6 and 16 features)
  - Linear Regression for price prediction (unsuccessful)
  - Three-pronged ("BUY", "SELL", "STAY"; tested alternatives)

RATIONALE FOR FEATURE SELECTION

Focus on usability and confidence to predict

- PCA was performed to see which variables would impact model to the greatest extent
  - Day, Month, Time
  - Forecasted temperature; historic average temperature
  - Dewpoint, precipitation, Atmospheric Pressure, Relative Humidity
  - Wind direction, wind chill, wind speed
- Three variables could potentially serve as good predictors; but are not capable of being accurately forecasted
  - Relative humidity
  - Precipitation and dewpoint

SELECTED VARIABLES
Month
Day
Time
Forecasted Temperature
Atmospheric Pressure
Difference of forecasted temperature from historic average temperature

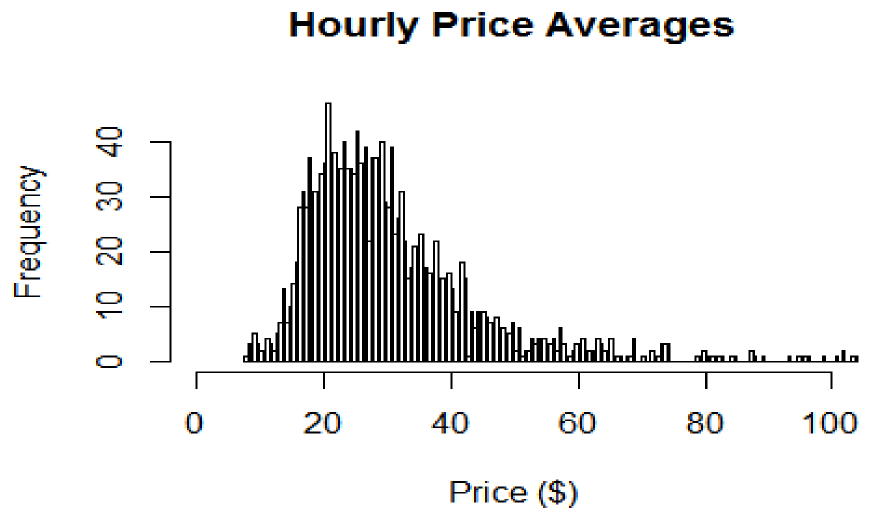
DATA ANALYSIS

Trained on historical data (2010 – 2016)

- Test predictions from January 2017 onward

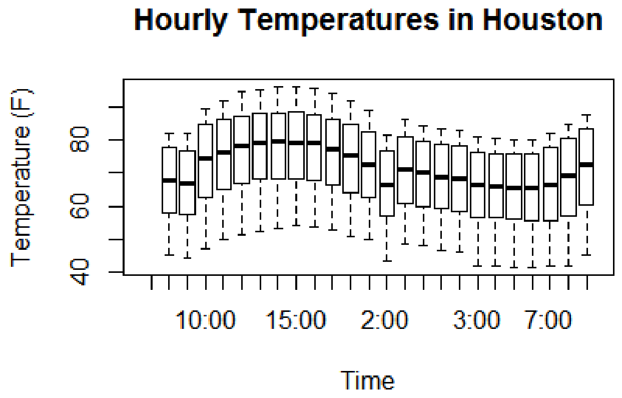
ERCOT: approximately 75,000 observations per month, over a span of 77 months (~5.775MM)

MRCC: hourly observations, since 2010 (54,191)

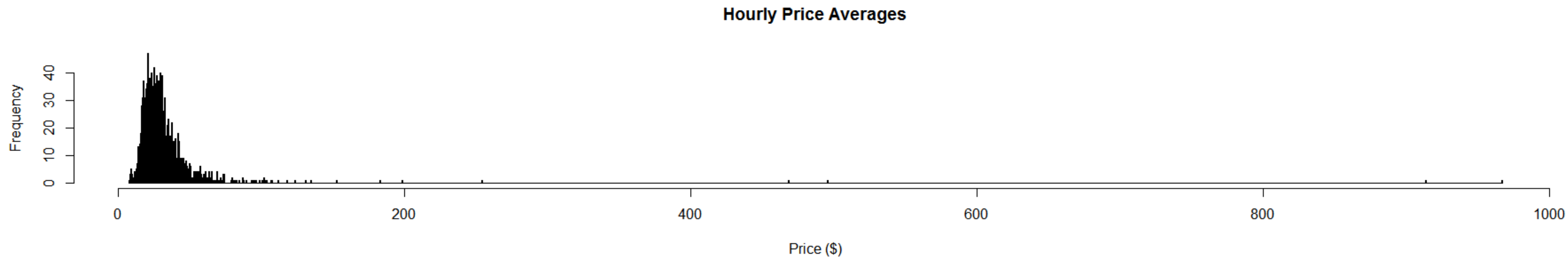


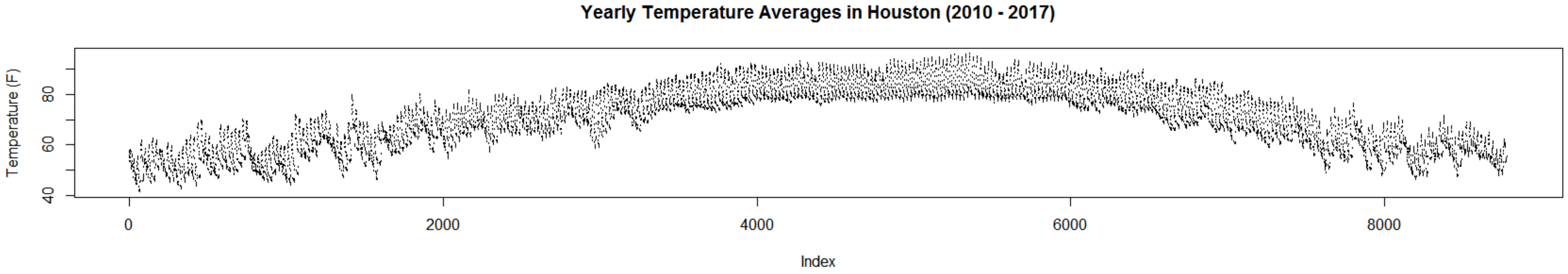
R Packages used:

- **lubridate**: to make manipulating dates / times simpler
- **darksky**: temperature forecasting
- **dplyr**: data manipulation
- **ggplot2**: visualization
- **C50**: decision tree algorithm
- **gmodels**: visualizing decision tree results with CrossTable()

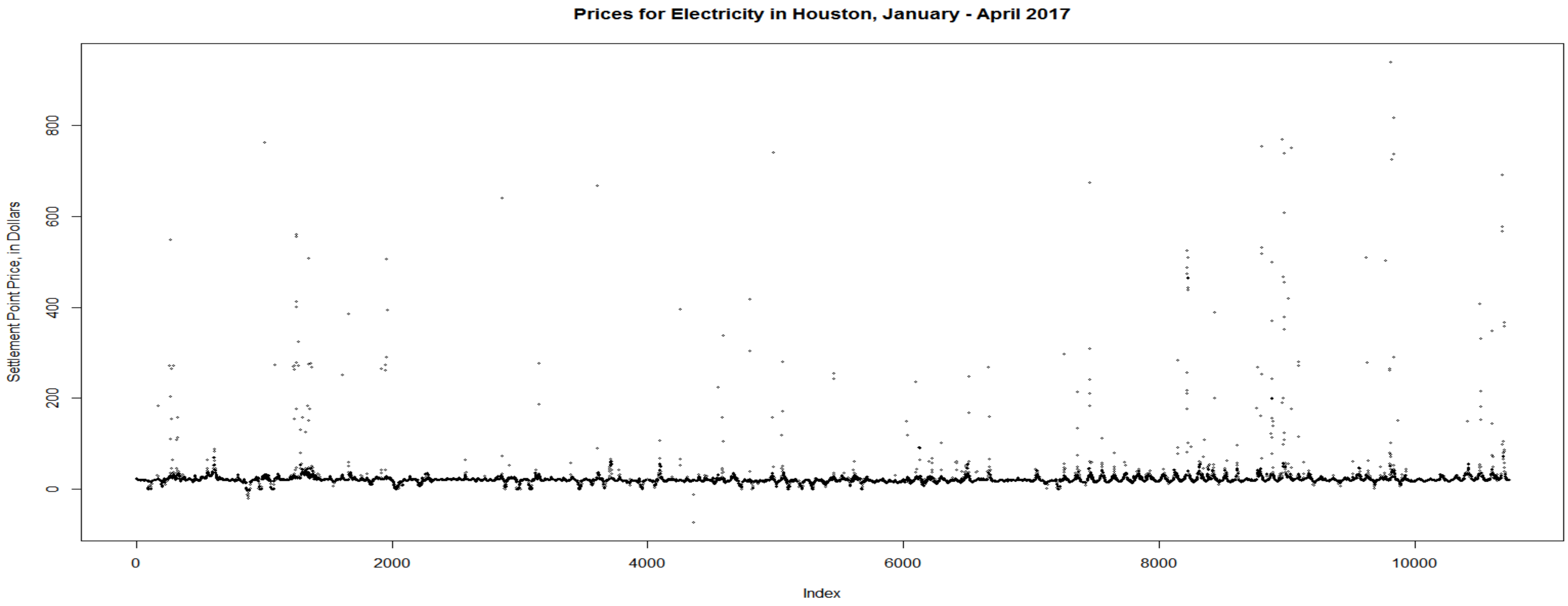


REMINDER: PRICE DISTRIBUTION IS EXTREMELY RIGHT-SKEWED!





ELECTRICITY PRICES IN HOUSTON (JANUARY 2017 – APRIL 2017)

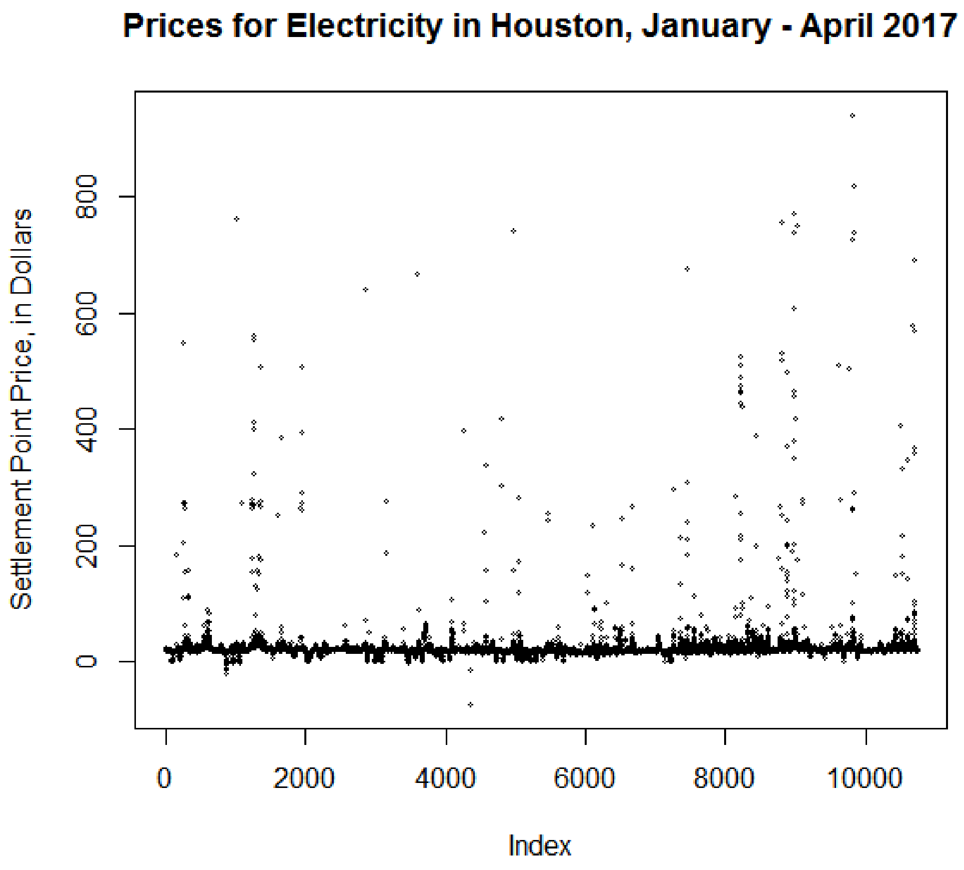


M1: ±0.5 STANDARD DEVIATIONS

```
Evaluation on training data (52774 cases):

Trial       Decision Tree
-----     ----------------
   Size        Errors

   0   1610 13472(25.5%)
   1    640 15688(29.7%)
   2    600 16824(31.9%)
   3    517 18222(34.5%)
   4    325 19730(37.4%)
   5    492 18261(34.6%)
   6    243 20999(39.8%)
   7    637 17201(32.6%)
   8    685 16383(31.0%)
   9    706 15180(28.8%)
boost        10979(20.8%)   <<
```

```
   (a)   (b)    <-classified as
  ----  ----
 24555  4329    (a): class BUY
  6650 17240    (b): class SELL


Attribute usage:

100.00% Temp..F.
100.00% Atm.Press..hPa.
 99.63% Day
 99.51% mean_temps
 99.37% Month
 98.57% Time


Time: 2.7 secs
```

```
Call:
C5.0.default(x = final_prod_2[1:6], y = final_prod_2$key, trials = 10)

Classification Tree
Number of samples: 52774
Number of predictors: 6

Number of boosting iterations: 10
Average tree size: 645.5
```

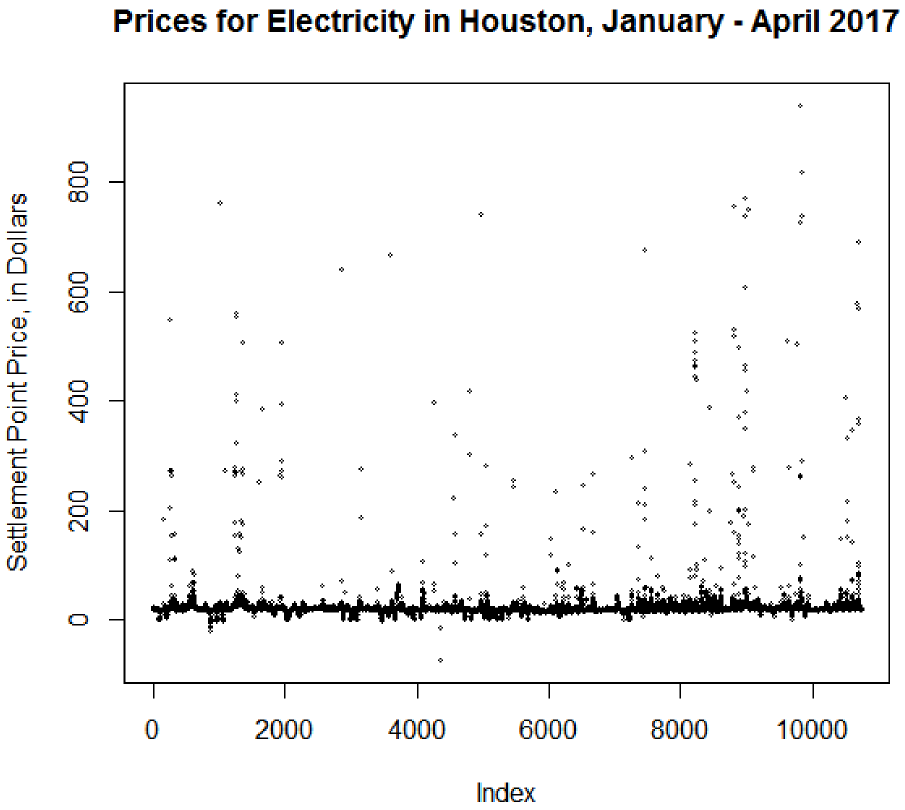


M2: THREE-PRONGED APPROACH FOR ±1 STANDARD DEVIATION

```
 Size      Errors

 0    693 12274(23.3%)
 1    258 14021(26.6%)
 2    497 14715(27.9%)
 3    521 15479(29.3%)
 4    571 16546(31.4%)
 5    579 16097(30.5%)
 6    609 17034(32.3%)
 7    513 14483(27.4%)
 8    465 13716(26.0%)
 9    386 13542(25.7%)
boost        11514(21.8%)   <<


   (a)   (b)   (c)    <-classified as
  ----  ----  ----
  1523  5171    29    (a): class BUY
   224 37556   350    (b): class HOLD
    28  5712  2181    (c): class SELL
```

```
Call:
C5.0.default(x = final_prod_2[1:6], y = as.factor(final_product$key2), trials = 10)

Classification Tree
Number of samples: 52774
Number of predictors: 6

Number of boosting iterations: 10
Average tree size: 509.2
```

```
   (a)   (b)   (c)    <-classified as
  ----  ----  ----
  1523  5171    29    (a): class BUY
   224 37556   350    (b): class HOLD
    28  5712  2181    (c): class SELL


Attribute usage:

100.00% Day
100.00% mean_temps
100.00% Temp..F.
100.00% Atm.Press..hPa.
 99.91% Month
 92.15% Time
```

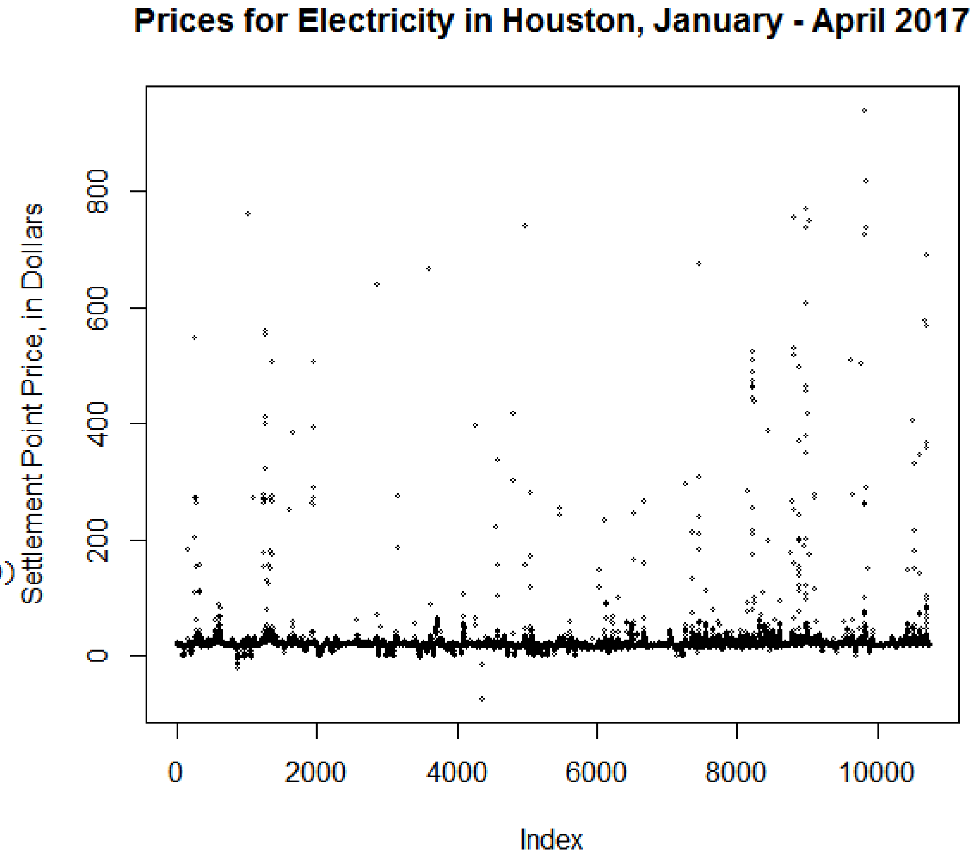


M3: ±2 STANDARD DEVIATIONS

```
Evaluation on training data (52774 cases):

Trial       Decision Tree
-----     -----------------
   Size        Errors

   0       99  1641( 3.1%)
   1       56  4628( 8.8%)
   2       76  4240( 8.0%)
   3      122  5120( 9.7%)
   4      102  5963(11.3%)
   5      136  5541(10.5%)
   6      108  3771( 7.1%)
   7       75  2870( 5.4%)
   8       69  2566( 4.9%)
   9       42  2084( 3.9%)
boost          1671( 3.2%)   <<
```

```
   (a)   (b)    <-classified as
  ----  ----
 50583    23    (a): class BUY
  1648   520    (b): class SELL


Attribute usage:

100.00% Month
100.00% mean_temps
100.00% Temp..F.
100.00% Atm.Press..hPa.
 99.96% Time
 99.45% Day


Time: 2.5 secs
```

```
Call:
C5.0.default(x = final_prod_2[1:6], y = as.factor(final_product$key3), trials = 10)

Classification Tree
Number of samples: 52774
Number of predictors: 6

Number of boosting iterations: 10
Average tree size: 88.5

Non-standard options: attempt to group attributes
```

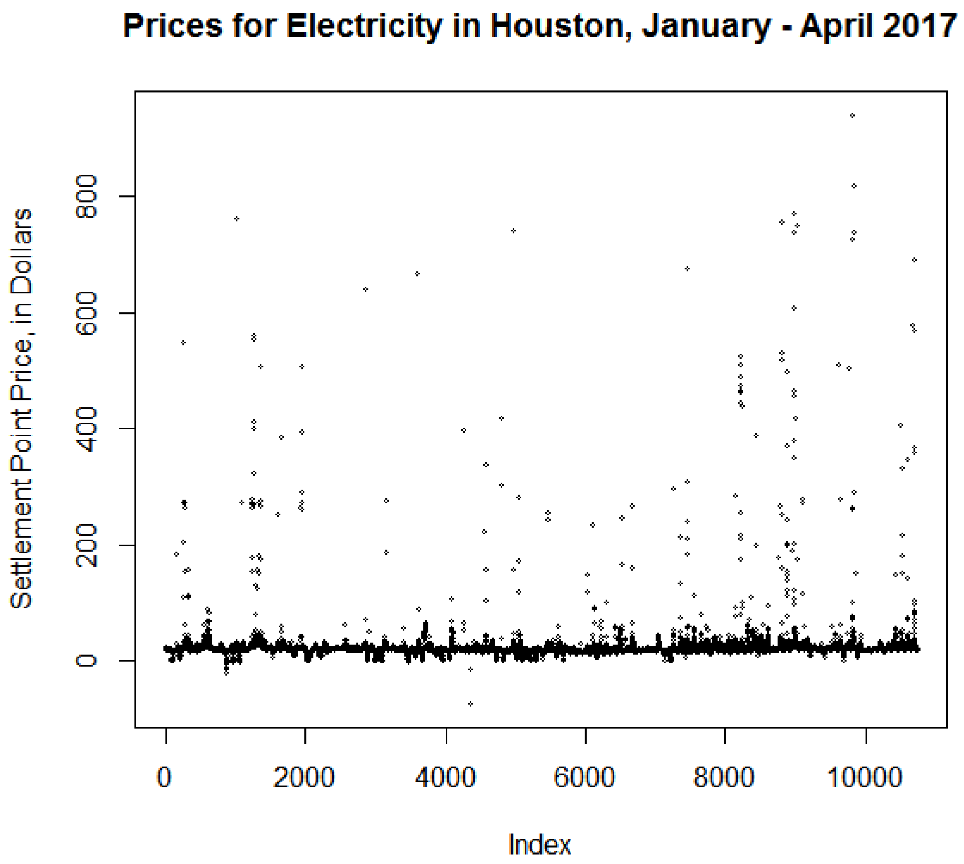


M4: ±1.5 STANDARD DEVIATIONS

```
Trial       Decision Tree
-----     -----------------
   Size         Errors

   0     119 3435( 6.5%)
   1      60 6598(12.5%)
   2     101 7280(13.8%)
   3      97 6404(12.1%)
   4     169 8779(16.6%)
   5     144 8161(15.5%)
   6     108 5490(10.4%)
   7      92 5068( 9.6%)
   8      71 4214( 8.0%)
   9      59 4081( 7.7%)
boost           3392( 6.4%)   <<
```

```
   (a)    (b)    <-classified as
  ----   ----
 48588    104    (a): class BUY
  3288    794    (b): class SELL


Attribute usage:

100.00% Month
100.00% mean_temps
100.00% Temp..F.
100.00% Atm.Press..hPa.
 99.65% Time
 95.95% Day
```

```
Call:
C5.0.default(x = final_prod_2[1:6], y = as.factor(final_product$key4), trials = 10)

Classification Tree
Number of samples: 52774
Number of predictors: 6

Number of boosting iterations: 10
Average tree size: 102
```

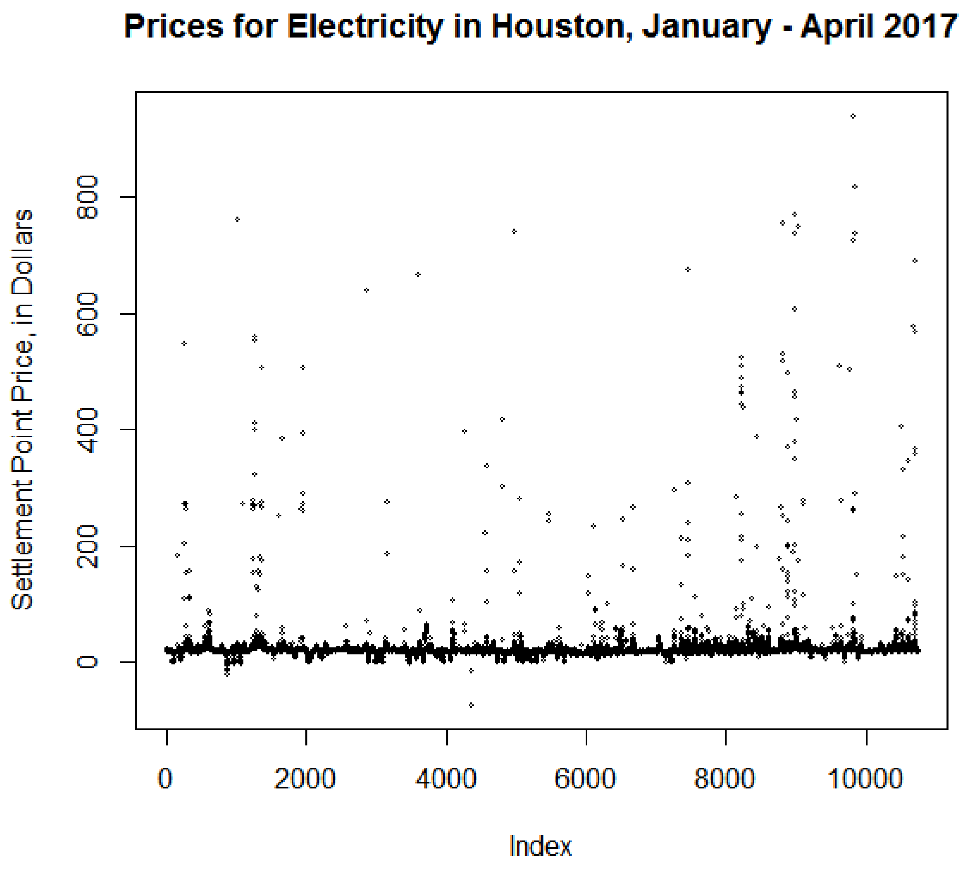


M5: ±1.25 STANDARD DEVIATIONS

```
Evaluation on training data (52774 cases):

Trial       Decision Tree
-----     -----------------
   Size        Errors

   0     158  4956( 9.4%)
   1      78  7027(13.3%)
   2     115  8151(15.4%)
   3     143 10746(20.4%)
   4     163 10541(20.0%)
   5     176 10538(20.0%)
   6     154  7414(14.0%)
   7     119  6891(13.1%)
   8     116  5706(10.8%)
   9      81  5687(10.8%)
boost          4711( 8.9%)   <<
```

```
  (a)   (b)    <-classified as
 ----  ----
46827   186    (a): class BUY
 4525  1236    (b): class SELL


Attribute usage:

100.00% Month
100.00% mean_temps
100.00% Temp..F.
100.00% Atm.Press..hPa.
 99.67% Day
 93.31% Time


Time: 2.5 secs
```

```
Call:
C5.0.default(x = final_prod_2[1:6], y = as.factor(final_product$key5), trials = 10)

Classification Tree
Number of samples: 52774
Number of predictors: 6

Number of boosting iterations: 10
Average tree size: 130.3
```

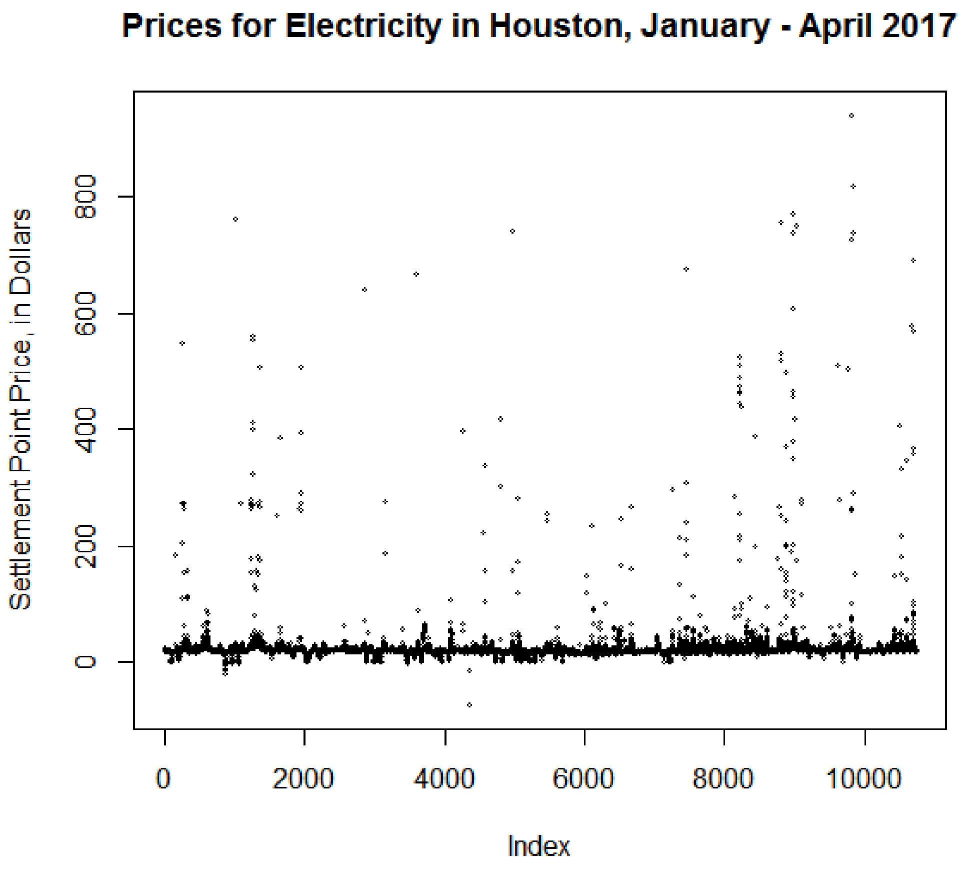


M6: ±1 STANDARD DEVIATIONS

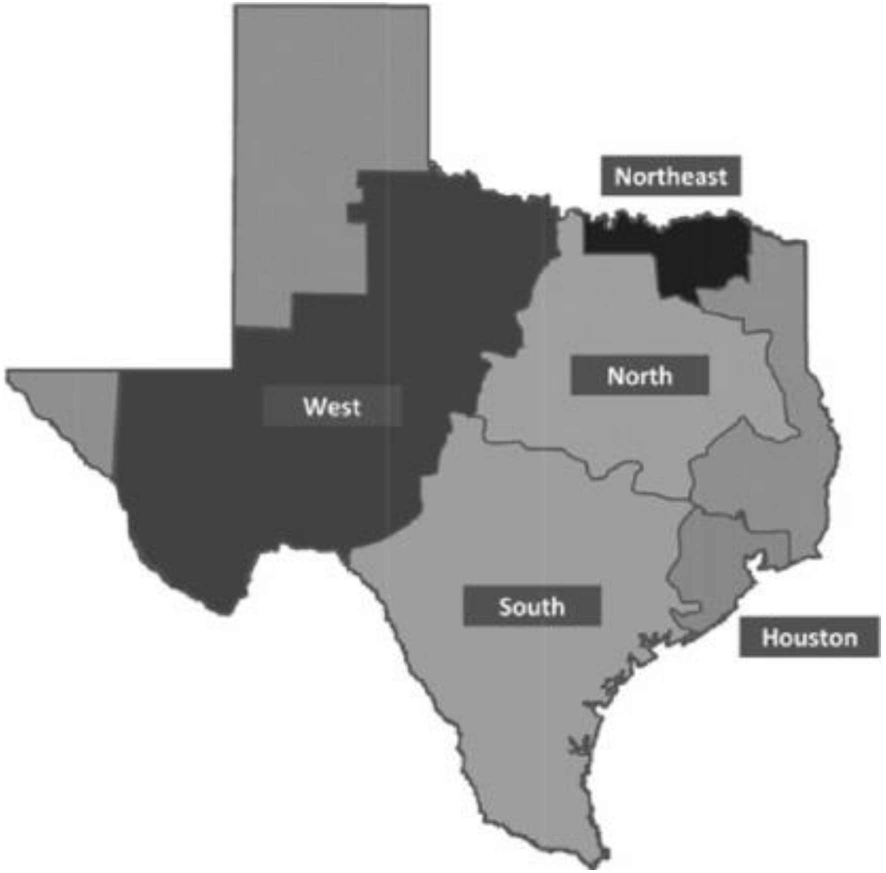
```
Evaluation on training data (52774 cases):

Trial       Decision Tree
-----     -----------------
   Size       Errors

   0    1612 13100(24.8%)
   1     592 16611(31.5%)
   2     465 17848(33.8%)
   3     438 19085(36.2%)
   4     537 17878(33.9%)
   5     263 21121(40.0%)
   6     303 20198(38.3%)
   7     294 19296(36.6%)
   8     687 15773(29.9%)
   9     785 14729(27.9%)
boost        11043(20.9%)   <<
```

```
   (a)   (b)    <-classified as
  ----  ----
 24319  4289    (a): class BUY
  6754 17412    (b): class SELL


Attribute usage:

100.00% Temp..F.
100.00% Atm.Press..hPa.
 99.80% Month
 99.55% mean_temps
 99.46% Day
 96.53% Time


Time: 2.7 secs
```

```
Call:
C5.0.default(x = final_prod_2[1:6], y = as.factor(final_product$key6), trials = 10)

Classification Tree
Number of samples: 52774
Number of predictors: 6

Number of boosting iterations: 10
Average tree size: 597.6
```



- How do **weather patterns** (humidity, precipitation, temperature) impact price of electricity for each of the hubs?
- What other **factors or combination of factors** impact electricity prices in other hubs? Are they similar, or are there regional variations?
  - Example: wind speed in West Texas
- What are the **optimal times** to purchase electricity at each of the hubs? To sell?
- How do **other factors** – for example, capacity – impact supply of electricity in Houston? How would that change, if new infrastructure is built to support the capacity?



FUTURE WORK / NEXT STEPS

QUESTIONS / SUGGESTIONS?