In [1]:

```
import requests
import json

betydb = "http://www.betydb.org/api/beta"
```

In [2]:

```
import pandas as pd
```

In [3]:

```
s4_df = pd.read_csv('/Users/curtislisle/Dropbox/ipython-notebooks/D3M/TERRA/terrare
f_r/season4date.csv')
```

```
/Users/curtislisle/anaconda3/lib/python3.7/site-packages/IPython/core/i
nteractiveshell.py:3057: DtypeWarning: Columns (18,32,35) have mixed ty
pes. Specify dtype option on import or set low_memory=False.
  interactivity=interactivity, compiler=compiler, result=result)
```

In [4]:

```
s4_df.head()['sitename']
```

Out[4]:

```
0     MAC Field Scanner Season 4 Range 8 Column 8
1     MAC Field Scanner Season 4 Range 8 Column 9
2    MAC Field Scanner Season 4 Range 8 Column 10
3    MAC Field Scanner Season 4 Range 8 Column 12
4     MAC Field Scanner Season 4 Range 9 Column 3
Name: sitename, dtype: object
```

In [5]:

```
s4_df.columns
```

Out[5]:

```
Index(['Unnamed: 0', 'checked', 'result_type', 'id', 'citation_id', 'si
te_id',
       'treatment_id', 'sitename', 'city', 'lat', 'lon', 'scientificnam
e',
       'commonname', 'genus', 'species_id', 'cultivar_id', 'author',
       'citation_year', 'treatment', 'date', 'time', 'raw_date', 'mont
h',
       'year', 'dateloc', 'trait', 'trait_description', 'mean', 'unit
s', 'n',
       'statname', 'stat', 'notes', 'access_level', 'cultivar', 'entit
y',
       'method_name', 'view_url', 'edit_url', 'trans_date'],
      dtype='object')
```

In [6]:

```
selected = ['id','cultivar','cultivar_id','date','trans_date','sitename','trait','m
ean','units']
s4sel = s4_df[selected]
```

In [7]:

```
s4sel.head()
```

Out[7]:

	id	cultivar	cultivar_id	date	trans_date	sitename	trait	mean	units
0	6004764469	PI570145	6000000961	2017 May 8	2017-05-08 12:00:00	MAC Field Scanner Season 4 Range 8 Column 8	canopy_height	13.0	cm
1	6004764470	PI329510	6000000577	2017 May 8	2017-05-08 12:00:00	MAC Field Scanner Season 4 Range 8 Column 9	canopy_height	14.0	cm
2	6004764471	PI510757	6000000850	2017 May 8	2017-05-08 12:00:00	MAC Field Scanner Season 4 Range 8 Column 10	canopy_height	12.0	cm
3	6004764473	PI329865	6000000815	2017 May 8	2017-05-08 12:00:00	MAC Field Scanner Season 4 Range 8 Column 12	canopy_height	13.0	cm
4	6004764478	PI569457	6000000935	2017 May 8	2017-05-08 12:00:00	MAC Field Scanner Season 4 Range 9 Column 3	canopy_height	14.0	cm

(**SKIP this cell... too slow**)

In [ ]:

```
s4sel['range'] = 0
s4sel['column'] = 0
s4sel['season'] = 0
count = 0

# loop through the entire dataframe and add values to the columns according to the
 sitename contents
for i in range(len(s4sel)):
    s4sel['season'][i] = int(s4sel['sitename'][i].split(' ')[4])
    s4sel['range'][i] = int(s4sel['sitename'][i].split(' ')[6])
    s4sel['column'][i] = int(s4sel['sitename'][i].split(' ')[8])
    count += 1
    if (count % 5000) == 0:
        print(count)
```

If all the measurements were equally distributed, doing a long to wide rollup mechanically using pandas' pivot would work. However, some measurements started later and ended earlier. Some measurements are daily, some are hourly (just in August), so we really need to split up this dataset into major subsets: daily and hourly, then try to pivot these datasets. Or worse, have to hand convert the entries. I elected to just write a custom algorithm to gather all the measurements together, indexed by date.

Write a routine that pivots/rolls up the data by hand, by creating a dictionary with trans_date as its index. Then we can add measurements one at a time...

In [8]:

```
s4hand = {}
count = 0
for i in range(len(s4sel)):
    #if count > 40:
    #    break
    #print(i,s4sel['trans_date'][i])

    # if we have never seen this date before, start a new dictionary at this date
    if s4sel['trans_date'][i] not in s4hand.keys():
        s4hand[s4sel['trans_date'][i]] = {}

    # if we have not seen this cultivar before on this date, then add a dictionary
 for this cultivar.  Is there is a chance we
    # might lose records here?
    if s4sel['cultivar_id'][i] not in s4hand[s4sel['trans_date'][i]].keys():
        s4hand[s4sel['trans_date'][i]][s4sel['cultivar_id'][i]] = {}

    # add this feature to the dictionary for the correct cultivar on this date.  We
add a dictionary entry named
    # from the contents in the 'trait' attribute and pull the value from the 'mean'
attribute.  This is the heart
    # of the long to wide format conversion.
    s4hand[s4sel['trans_date'][i]][s4sel['cultivar_id'][i]][s4sel['trait'][i]] = s4
sel['mean'][i]

    # add the cultivar and the location (split out from the sitename text).  This w
ill be added multiple times,
    # so represents redundant processing, but it works to place the measurements in
cultivar and location
    s4hand[s4sel['trans_date'][i]][s4sel['cultivar_id'][i]]['cultivar_id'] = s4sel[
'cultivar_id'][i]
    s4hand[s4sel['trans_date'][i]][s4sel['cultivar_id'][i]]['season'] = int(s4sel[
'sitename'][i].split(' ')[4])
    s4hand[s4sel['trans_date'][i]][s4sel['cultivar_id'][i]]['range'] = int(s4sel['s
itename'][i].split(' ')[6])
    s4hand[s4sel['trans_date'][i]][s4sel['cultivar_id'][i]]['column'] = int(s4sel[
'sitename'][i].split(' ')[8])
    count += 1
print('entered ',count, 'measurements')
```

```
entered  372363 measurements
```

In [133]:

```
print('how many different datetime events:')
print(len(s4hand.keys()))
#print(s4hand.keys())
print('print ouf the wide tuple of a particular cultivar at a particular datetime:'
)
print(s4hand['2017-07-08 12:00:00'][6000000861])
print(s4hand['2017-08-08 12:00:00'][6000000861])
```

```
how many different datetime events:
3152
print ouf the wide tuple of a particular cultivar at a particular datet
ime:
{'canopy_height': 192.0, 'cultivar_id': 6000000861, 'season': 4, 'rang
e': 46, 'column': 3, 'leaf_angle_mean': 0.46521782152400004, 'leaf_angl
e_alpha': 1.6835253597400002, 'leaf_angle_beta': 1.4356619889500002, 'l
eaf_angle_chi': 1.71004921126}
{'canopy_height': 293.0, 'cultivar_id': 6000000861, 'season': 4, 'rang
e': 46, 'column': 3, 'leaf_angle_mean': 0.460059049579, 'leaf_angle_alp
ha': 1.80939043311, 'leaf_angle_beta': 1.5116882921700001, 'leaf_angle_
chi': 1.7059298014200002}
```

So, at this point, we have a dictionary (s4hand) which has keys for each different datetime a measurement was entered. There are 3152 different datetime entries. This includes all the dates in August where hand measurements are made. This dictionary can't be scanned in datetime order, but it has accumulated all the tuples. A single dataframe could be made from this dictionary, but a lot of the entries would be empty, since most datetime entries only contain a subset of the measurements.

If the tuples were the same size, we could generate a full pandas dataframe from this dictionary, using the datetime as the index. However, some tuples are wider than others, since not all measurements were made each time. After reviewing this data distribution, it seems best to create subdictionaries for a certain date range with consistent entries, and then convert the subdictionaries to dataframes.

In [69]:

```
for i in s4hand.keys():
    if i >= '2017-08-01' and i <= '2017-08-03':
        print(i)
```

```
2017-08-02 12:00:00
2017-08-02 13:34:00
2017-08-02 13:32:00
2017-08-02 12:10:00
2017-08-02 12:09:00
2017-08-02 11:03:00
2017-08-02 11:01:00
2017-08-02 13:28:00
2017-08-02 13:46:00
2017-08-02 13:45:00
2017-08-02 13:43:00
2017-08-02 13:42:00
2017-08-02 13:38:00
2017-08-02 12:01:00
2017-08-02 11:16:00
2017-08-02 11:13:00
2017-08-02 13:31:00
2017-08-02 12:14:00
2017-08-02 12:13:00
2017-08-02 12:11:00
2017-08-02 12:08:00
2017-08-02 11:07:00
2017-08-02 11:05:00
2017-08-02 11:00:00
2017-08-02 13:36:00
2017-08-02 13:35:00
2017-08-02 13:33:00
2017-08-02 10:26:00
2017-08-02 10:29:00
2017-08-02 10:30:00
2017-08-02 10:36:00
2017-08-02 10:42:00
2017-08-02 10:49:00
2017-08-02 10:55:00
2017-08-02 11:29:00
2017-08-02 11:31:00
2017-08-02 11:34:00
2017-08-02 11:41:00
2017-08-02 11:45:00
2017-08-02 11:46:00
2017-08-02 11:51:00
2017-08-02 11:53:00
2017-08-02 11:54:00
2017-08-02 11:57:00
2017-08-02 12:20:00
2017-08-02 12:33:00
2017-08-02 12:34:00
2017-08-02 12:53:00
2017-08-02 13:01:00
2017-08-02 13:03:00
2017-08-02 13:06:00
2017-08-02 13:07:00
2017-08-02 13:10:00
2017-08-02 13:17:00
2017-08-02 13:20:00
2017-08-02 13:21:00
2017-08-02 13:22:00
```

```
2017-08-02 13:24:00
2017-08-02 13:54:00
2017-08-02 13:55:00
2017-08-02 13:44:00
2017-08-02 13:40:00
2017-08-02 12:05:00
2017-08-02 12:04:00
2017-08-02 12:03:00
2017-08-02 11:59:00
2017-08-02 11:15:00
2017-08-02 11:11:00
2017-08-02 11:10:00
2017-08-02 10:27:00
2017-08-02 10:31:00
2017-08-02 10:35:00
2017-08-02 10:37:00
2017-08-02 10:47:00
2017-08-02 10:43:00
2017-08-02 10:41:00
2017-08-02 10:39:00
2017-08-02 10:50:00
2017-08-02 10:54:00
2017-08-02 10:57:00
2017-08-02 11:28:00
2017-08-02 11:30:00
2017-08-02 11:43:00
2017-08-02 11:44:00
2017-08-02 11:47:00
2017-08-02 11:50:00
2017-08-02 11:52:00
2017-08-02 12:18:00
2017-08-02 12:19:00
2017-08-02 12:22:00
2017-08-02 12:23:00
2017-08-02 12:24:00
2017-08-02 12:31:00
2017-08-02 12:32:00
2017-08-02 12:36:00
2017-08-02 12:54:00
2017-08-02 12:55:00
2017-08-02 12:56:00
2017-08-02 12:57:00
2017-08-02 13:02:00
2017-08-02 13:11:00
2017-08-02 13:52:00
2017-08-02 13:53:00
```

So August 2nd at noon (not August 1st) is when measurements started being taken every few minutes. Lets look at a few...

In [134]:

```
print('there are', len(s4hand['2017-08-02 13:52:00'][6000000962].keys()), 'keys in
 this observation:')
s4hand['2017-08-02 13:52:00']
```

```
there are 42 keys in this observation:
```

Out[134]:


```
{6000000962: {'absorbance_850': 0.41700000000000004,
  'cultivar_id': 6000000962,
  'season': 4,
  'range': 45,
  'column': 4,
  'roll': -14.82,
  'PhiNO': 0.14400000000000002,
  'PhiNPQ': 0.6,
  'absorbance_530': 1.2,
  'absorbance_605': 1.466,
  'absorbance_730': 0.376,
  'absorbance_880': 0.46,
  'absorbance_940': 0.46,
  'Fs': 4298.7,
  'NPQt': 4.154,
  'qL': 0.363,
  'qP': 0.526,
  'RFd': 0.344,
  'SPAD_530': 73.96,
  'SPAD_605': 100.57,
  'SPAD_730': -8.39,
  'leaf_thickness': 0.28,
  'ambient_humidity': 39.557617,
  'leaf_angle_clamp_position': 14.87,
  'pitch': -1.28,
  'proximal_air_temperature': 40.139998999999996,
  'FvP/FmP': 0.486,
  'gH+': 0.0,
  'ECSt': 0.0,
  'leaf_temperature_differential': -6.329999,
  'Phi2': 0.256,
  'relative_chlorophyll': 48.84512428,
  'FmPrime': 5777.98,
  'FoPrime': 2968.0,
  'LEF': 174.076,
  'SPAD_420': 164.67,
  'SPAD_650': 48.85,
  'SPAD_850': -4.34,
  'SPAD_880': 0.01,
  'light_intensity_PAR': 1511.0,
  'vH+': 0.0,
  'leaf_temperature': 306.96}}
```

In [297]:

```
print('there are', len(s4hand['2017-08-02 13:53:00'][6000000962].keys()), 'keys in
 this observation:')
s4hand['2017-08-02 13:53:00']
```

there are 27 keys in this observation:

Out[297]:


```
{6000000962: {'absorbance_850': 0.41200000000000003,
  'cultivar_id': 6000000962,
  'season': 4,
  'range': 45,
  'column': 4,
  'roll': 28.54,
  'PhiNO': 0.221,
  'PhiNPQ': 0.54,
  'absorbance_530': 1.094,
  'absorbance_605': 1.348,
  'absorbance_730': 0.36200000000000004,
  'absorbance_880': 0.461,
  'absorbance_940': 0.457,
  'Fs': 5446.8,
  'NPQt': 2.447,
  'qL': 0.222,
  'qP': 0.408,
  'RFd': 0.314,
  'SPAD_530': 63.77,
  'SPAD_605': 89.11,
  'SPAD_730': -9.46,
  'leaf_thickness': 0.25,
  'ambient_humidity': 39.856445,
  'leaf_angle_clamp_position': 32.96,
  'pitch': 17.23,
  'cultivar': 6000000962,
  'date': '2017-08-02 13:53:00'}}
```

In [298]:

```
print('there are', len(s4hand['2017-08-02 13:11:00'][6000000851].keys()), 'keys in
 this observation:')
s4hand['2017-08-02 13:11:00']
```

there are 40 keys in this observation:

Out[298]:


```
{6000000851: {'absorbance_850': 0.396,
  'cultivar_id': 6000000851,
  'season': 4,
  'range': 26,
  'column': 15,
  'roll': -55.82,
  'PhiNO': 0.195,
  'PhiNPQ': 0.51,
  'absorbance_530': 1.131,
  'absorbance_605': 1.374,
  'absorbance_730': 0.35700000000000004,
  'absorbance_880': 0.446,
  'absorbance_940': 0.441,
  'Fs': 4951.5,
  'NPQt': 2.617,
  'qL': 0.31,
  'qP': 0.513,
  'RFd': 0.418,
  'SPAD_530': 69.06,
  'SPAD_605': 93.29,
  'SPAD_730': -8.34,
  'leaf_thickness': 0.1,
  'ambient_humidity': 39.974609,
  'leaf_angle_clamp_position': 57.04,
  'pitch': 14.43,
  'proximal_air_temperature': 39.82,
  'FvP/FmP': 0.574,
  'leaf_temperature_differential': -1.63,
  'Phi2': 0.295,
  'relative_chlorophyll': 46.43594646,
  'FmPrime': 7021.161999999999,
  'FoPrime': 2989.0,
  'LEF': 141.406,
  'SPAD_420': 158.94,
  'SPAD_650': 46.44,
  'SPAD_850': -4.48,
  'SPAD_880': 0.47,
  'light_intensity_PAR': 1066.0,
  'cultivar': 6000000851,
  'date': '2017-08-02 13:11:00'}}
```


try generating histograms of the tuple width

lets explore the coverage of the dictionary by cycling through it and listing how many measurements are on each day and build a histogram of the measurement count. **this is not correct because of the cultivar key**

In [87]:

```
histo_date = {}
for key in s4hand.keys():
    # how many measurements are on this datetime. accumulate in a histogram diction
ary
    length = len(s4hand[key])
    if length not in histo_date.keys():
        histo_date[length] =  1
    else:
        histo_date[length] += 1
print(histo_date)
```

```
{244: 1, 159: 1, 1: 3002, 185: 1, 188: 1, 351: 49, 313: 1, 48: 1, 296:
2, 30: 1, 127: 1, 131: 1, 146: 1, 339: 1, 70: 1, 289: 1, 287: 1, 73: 1,
292: 1, 220: 1, 349: 11, 329: 1, 344: 2, 270: 2, 332: 2, 278: 1, 337:
1, 283: 1, 318: 1, 341: 1, 84: 1, 120: 1, 82: 1, 197: 1, 140: 1, 324:
2, 336: 2, 326: 1, 334: 1, 331: 1, 251: 1, 177: 1, 35: 7, 19: 1, 52: 2,
42: 1, 224: 1, 18: 9, 55: 2, 63: 2, 346: 1, 275: 1, 262: 1, 15: 1, 13:
2, 333: 1, 328: 1, 304: 1, 3: 1, 76: 1, 203: 1, 72: 1, 50: 1, 142: 1, 1
39: 1, 102: 1, 107: 1, 27: 1, 17: 1}
```

In [78]:

```
import heapq
from itertools import count
cnt = count()
heap = []
for key in histo_date:
    heapq.heappush(heap, (histo_date[key], next(cnt), key))
#heap
heapq.nlargest(10, heap, key=None)
```

Out[78]:

```
[(3002, 2, 1),
 (49, 5, 351),
 (11, 20, 349),
 (9, 47, 18),
 (7, 42, 35),
 (2, 54, 13),
 (2, 49, 63),
 (2, 48, 55),
 (2, 44, 52),
 (2, 36, 336)]
```

it might make more sense to organize the heap with the number of elements first...

In [81]:

```
import heapq
from itertools import count
cnt = count()
heap = []
for key in histo_date:
    heapq.heappush(heap, (key,  next(cnt), histo_date[key]))
#heap
heapq.nlargest(20, heap, key=None)
```

Out[81]:

```
[(351, 5, 49),
 (349, 20, 11),
 (346, 50, 1),
 (344, 22, 2),
 (341, 29, 1),
 (339, 13, 1),
 (337, 26, 1),
 (336, 36, 2),
 (334, 38, 1),
 (333, 55, 1),
 (332, 24, 2),
 (331, 39, 1),
 (329, 21, 1),
 (328, 56, 1),
 (326, 37, 1),
 (324, 35, 2),
 (318, 28, 1),
 (313, 6, 1),
 (304, 57, 1),
 (296, 8, 2)]
```

Extract date regions of consistent measurements

Going back to filtering the original event dictionary, lets try to make a dataframe of only the August timeframe (where many hand-made measurements were taken). There are 4573 entries without filtering.

In [154]:

```
augustList = []
dateList = []
for key in s4hand.keys():
    if (key > '2017-08-02 00:00:00') and (key < '2017-08-31 00:00:00'):
        cultivar_keys = s4hand[key].keys()
        for k in cultivar_keys:
            record = s4hand[key][k]
            if (record.keys())>30:
                #print(key)
                #print(record)
                #break
                record['cultivar'] = k
                record['date'] = key
                # delete columns that are missing data
                if 'ECSt' in record:
                    del record['ECSt']
                if 'gH+' in record:
                    del record['gH+']
                if 'vH+' in record:
                    del record['vH+']
                if 'absorbance_420' in record:
                    del record['absorbance_420']
                if 'absorbance_650' in record:
                    del record['absorbance_650']
                augustList.append(record)
                dateList.append(key)
        #break
print(len(augustList))
```

```
949
```

In [155]:

```
import pandas as pd
august_df = pd.DataFrame(augustList,index=dateList)
august_df.head()
```

Out[155]:

	FmPrime	FoPrime	Fs	FvP/FmP	LEF	NPQt	Phi2	PhiNO	PhiNPQ	RFd	...
2017-08-28 12:00:00	2986.150	2233.0	2316.8	0.252	157.363	13.480	0.224	0.054	0.722	0.289	...
2017-08-28 11:14:00	4181.791	2583.0	3221.0	0.382	158.183	6.886	0.230	0.098	0.673	0.298	...
2017-08-28 11:15:00	5116.053	2321.0	3569.2	0.546	177.017	3.051	0.302	0.172	0.525	0.433	...
2017-08-28 11:59:00	1902.247	1759.0	1757.1	0.076	53.598	58.729	0.076	0.015	0.908	0.083	...
2017-08-28 12:10:00	1749.371	1476.0	1512.8	0.156	94.147	25.393	0.135	0.033	0.832	0.156	...

5 rows × 41 columns

In [156]:

```
august_df.columns
```

Out[156]:

```
Index(['FmPrime', 'FoPrime', 'Fs', 'FvP/FmP', 'LEF', 'NPQt', 'Phi2', 'P
hiNO',
       'PhiNPQ', 'RFd', 'SPAD_420', 'SPAD_530', 'SPAD_605', 'SPAD_650',
       'SPAD_730', 'SPAD_850', 'SPAD_880', 'absorbance_530', 'absorbanc
e_605',
       'absorbance_730', 'absorbance_850', 'absorbance_880', 'absorbanc
e_940',
       'ambient_humidity', 'column', 'cultivar', 'cultivar_id', 'date',
       'leaf_angle_clamp_position', 'leaf_temperature',
       'leaf_temperature_differential', 'leaf_thickness',
       'light_intensity_PAR', 'pitch', 'proximal_air_temperature', 'q
L', 'qP',
       'range', 'relative_chlorophyll', 'roll', 'season'],
      dtype='object')
```

In [158]:

```
august_df.to_csv("s4_august_by_hand_30plus.csv",index=False)
```

Go back and look at the records during this period that have fewer entries:

In [173]:

```
augustListSmall = []
dateListSmall = []
for key in s4hand.keys():
    if (key > '2017-08-02 00:00:00') and (key < '2017-08-31 00:00:00'):
        cultivar_keys = s4hand[key].keys()
        for k in cultivar_keys:
            record = s4hand[key][k]
            if len(record.keys()) == 9:
                #print(key)
                #print(record)
                #break
                record['cultivar'] = k
                record['date'] = key
                # delete columns that are missing data
                if 'ECSt' in record:
                    del record['ECSt']
                if 'gH+' in record:
                    del record['gH+']
                if 'flavonol_index' in record:
                    del record['flavonol_index']
                if 'NBI_nitrogen_balance_index' in record:
                    del record['NBI_nitrogen_balance_index']
                if 'chlorophyll_index' in record:
                    del record['chlorophyll_index']
                if 'absorbance_730' not in record:
                    augustListSmall.append(record)
                    dateListSmall.append(key)
        #break
print(len(augustListSmall))
```

```
533
```

In [174]:

```
import pandas as pd
august_short_df = pd.DataFrame(augustListSmall,index=dateListSmall)
august_short_df.head()
```

Out[174]:

	column	cultivar	cultivar_id	date	panicle_count	panicle_surface_area	panicle_
2017-08-21 12:00:00	12	6000001059	6000001059	2017-08-21 12:00:00	8.0	16033.582107	99161
2017-08-21 12:00:00	6	6000000214	6000000214	2017-08-21 12:00:00	4.0	8154.624339	37914
2017-08-21 12:00:00	10	6000000919	6000000919	2017-08-21 12:00:00	5.0	20663.535212	160338
2017-08-21 12:00:00	6	6000000739	6000000739	2017-08-21 12:00:00	46.0	11581.658116	72110
2017-08-21 12:00:00	7	6000000945	6000000945	2017-08-21 12:00:00	16.0	19284.814669	165901

In [175]:

```
august_short_df.columns
```

Out[175]:

```
Index(['column', 'cultivar', 'cultivar_id', 'date', 'panicle_count',
       'panicle_surface_area', 'panicle_volume', 'range', 'season'],
      dtype='object')
```

In [176]:

```
august_short_df.to_csv("s4_august_by_hand_panicle.csv",index=False)
```

In [ ]:

```

```

In [183]:

```
augustListSmall = []
dateListSmall = []
for key in s4hand.keys():
    if (key > '2017-08-02 00:00:00') and (key < '2017-08-31 00:00:00'):
        cultivar_keys = s4hand[key].keys()
        for k in cultivar_keys:
            record = s4hand[key][k]
            if 'canopy_height' in record and ('leaf_angle_alpha' in record):
                #print(key)
                #print(record)
                #break
                # delete columns that are missing data
                if 'panicle_count' in record:
                    del record['panicle_count']
                if 'panicle_surface_area' in record:
                    del record['panicle_surface_area']
                if 'panicle_volume' in record:
                    del record['panicle_volume']
                if 'surface_temperature' in record:
                    del record['surface_temperature']
                if 'chlorophyll_index' in record:
                    del record['chlorophyll_index']
                if 'absorbance_730' not in record:
                    augustListSmall.append(record)
                    dateListSmall.append(key)
        #break
print(len(augustListSmall))
```

```
1531
```

In [184]:

```
import pandas as pd
august_short_df = pd.DataFrame(augustListSmall,index=dateListSmall)
august_short_df.head()
```

Out[184]:

	canopy_height	column	cultivar	cultivar_id	date	leaf_angle_alpha	leaf_angle_l
2017-08-21 12:00:00	347.0	12	6000001055	6000001055	2017-08-21 12:00:00	1.647406	1.38(
2017-08-21 12:00:00	342.0	9	6000001054	6000001054	2017-08-21 12:00:00	1.929799	1.58
2017-08-22 12:00:00	329.0	6	6000000552	6000000552	2017-08-22 12:00:00	1.882103	1.39
2017-08-22 12:00:00	338.0	7	6000000710	6000000710	2017-08-22 12:00:00	1.565166	1.35(
2017-08-22 12:00:00	287.0	13	6000001009	6000001009	2017-08-22 12:00:00	1.147330	1.11

In [ ]:

```
```

In [185]:

```
august_short_df.to_csv("s4_august_by_hand_leaf.csv",index=False)
```

In [187]:

```
augustListSmall = []
dateListSmall = []
for key in s4hand.keys():
    if (key > '2017-08-02 00:00:00') and (key < '2017-08-31 00:00:00'):
        cultivar_keys = s4hand[key].keys()
        for k in cultivar_keys:
            record = s4hand[key][k]
            if ('canopy_height' in record) and ('leaf_angle_alpha' in record) and (
'panicle_count' in record):
                #print(key)
                #print(record)
                #break
                # delete columns that are missing data
                if 'surface_temperature' in record:
                    del record['surface_temperature']
                if 'chlorophyll_index' in record:
                    del record['chlorophyll_index']
                if 'absorbance_730' in record:
                    del record['chlorophyll_index']
                augustListSmall.append(record)
                dateListSmall.append(key)
        #break
print(len(augustListSmall))
```

```
0
```

So there aren't any entries during August that have both panicle data and leaf data in the same measurement. These are probably listed under different datetime values...sigh. Pivot back to the full dataset and extract as many full tuples as possible...

In [9]:

```
augustListFull = []
dateListFull = []
for key in s4hand.keys():
    cultivar_keys = s4hand[key].keys()
    for k in cultivar_keys:
        record = s4hand[key][k]
        if ('canopy_height' in record) and ('leaf_angle_alpha' in record) and ('lea
f_angle_beta' in record):
            record['cultivar'] = k
            record['date'] = key
            #print(key)
            #print(record)
            #break
            # delete columns that are missing data
            if 'panicle_count' in record:
                del record['panicle_count']
            if 'panicle_surface_area' in record:
                del record['panicle_surface_area']
            if 'panicle_volume' in record:
                del record['panicle_volume']
            if 'surface_temperature' in record:
                del record['surface_temperature']
            if 'chlorophyll_index' in record:
                del record['chlorophyll_index']
            if 'leaf_temperature' in record:
                del record['leaf_temperature']
            if 'absorbance_730' in record:
                del record['chlorophyll_index']
            if 'cultivar_id' in record:
                del record['cultivar_id']
            augustListFull.append(record)
            dateListFull.append(key)
        #break
print(len(augustListFull))

full_df = pd.DataFrame(augustListFull,index=dateListFull)
full_df.head()
```

```
9441
```

Out[9]:

	canopy_height	column	cultivar	date	leaf_angle_alpha	leaf_angle_beta	leaf_an
2017-05-13 12:00:00	15.0	2	6000000836	2017-05-13 12:00:00	2.695956	1.977380	1.
2017-05-13 12:00:00	15.0	15	6000000462	2017-05-13 12:00:00	3.265980	2.018623	1.
2017-05-13 12:00:00	19.0	2	6000000751	2017-05-13 12:00:00	2.159610	1.809209	1.
2017-05-13 12:00:00	13.0	4	6000000916	2017-05-13 12:00:00	3.042180	2.198751	1.
2017-05-15 12:00:00	17.0	2	6000000976	2017-05-15 12:00:00	2.305345	1.872028	1.

In [27]:

```
full_df.describe()
```

Out[27]:

	canopy_height	column	cultivar	leaf_angle_alpha	leaf_angle_beta	leaf_angle_ch
count	9441.000000	9441.000000	9.441000e+03	9441.000000	9441.000000	9441.00000
mean	197.719203	8.541468	6.000001e+09	2.903153	1.825797	1.90866
std	96.712778	4.004024	2.002971e+02	1.076542	0.321239	0.24367
min	12.000000	1.000000	6.000000e+09	0.756692	0.977342	0.75673
25%	114.000000	5.000000	6.000001e+09	2.103990	1.590333	1.76743
50%	208.000000	9.000000	6.000001e+09	2.846314	1.817881	1.90602
75%	271.000000	12.000000	6.000001e+09	3.540884	2.040797	2.04827
max	412.000000	16.000000	6.000001e+09	8.647608	4.171909	4.76868

In [199]:

```
full_df.to_csv("s4_full_height_leaf.csv",index=False)
```

In [28]:

```
def returnUniqueCounts(dframe):
    return pd.DataFrame.from_records([(col, dframe[col].nunique()) for col in dfram
e.columns],
                                    columns=['Column_Name', 'Num_Unique']).sort_values(by=['N
um_Unique'])
```

In [29]:

```
returnUniqueCounts(full_df)
```

Out[29]:

	Column_Name	Num_Unique
9	season	1
1	column	16
8	range	53
3	date	55
10	day_offset	55
2	cultivar	351
0	canopy_height	395
4	leaf_angle_alpha	9441
5	leaf_angle_beta	9441
6	leaf_angle_chi	9441
7	leaf_angle_mean	9441

convert the date to a day offset into the year, so we can get an integer to pass into a model.

In [30]:

```
full_df.dtypes
```

Out[30]:

```
canopy_height                float64
column                         int64
cultivar                       int64
date                  datetime64[ns]
leaf_angle_alpha             float64
leaf_angle_beta              float64
leaf_angle_chi               float64
leaf_angle_mean              float64
range                          int64
season                         int64
day_offset           timedelta64[ns]
dtype: object
```

In [20]:

```
full_df['date'] = pd.to_datetime(full_df['date'])
```

In [21]:

```
from datetime import datetime
print(datetime.strptime('2017-05-01 12:00:00', '%Y-%m-%d %H:%M:%S'))
```

```
2017-05-01 12:00:00
```

In [43]:

```
# add an offset column that subtracts a "start date" from each of the datetimes in
 the samples.  This will give us an offset in days
full_df['day_offset'] = full_df['date'] - datetime.strptime('2017-05-01 12:00:00',
'%Y-%m-%d %H:%M:%S')
```

In [44]:

```
# here is how a timedelta offset is converted to its component part
full_df['day_offset'][0].days
```

Out[44]:

```
12
```

In [45]:

```
# pandas series don't like the df['column'].dt.days notation, so just convert to an
int. Divide by the number of microseconds in a day
full_df['day_offset'] = full_df['day_offset'].astype('int64')/ 86400000000000
full_df.head()
```

Out[45]:

	canopy_height	column	cultivar	date	leaf_angle_alpha	leaf_angle_beta	leaf_an
2017-05-13 12:00:00	15.0	2	6000000836	2017-05-13 12:00:00	2.695956	1.977380	1.
2017-05-13 12:00:00	15.0	15	6000000462	2017-05-13 12:00:00	3.265980	2.018623	1.
2017-05-13 12:00:00	19.0	2	6000000751	2017-05-13 12:00:00	2.159610	1.809209	1.
2017-05-13 12:00:00	13.0	4	6000000916	2017-05-13 12:00:00	3.042180	2.198751	1.
2017-05-15 12:00:00	17.0	2	6000000976	2017-05-15 12:00:00	2.305345	1.872028	1.

In [246]:

```
full_df.to_csv("s4_full_height_leaf_day.csv",index=False)
```

look at how grouping measurements by cultivar and location could be done

In [247]:

```
len(full_df.groupby(['cultivar','column','range']).groups)
```

Out[247]:

```
727
```

In [248]:

```
print(full_df.groupby(['cultivar','column','range']).groups[(6000000207, 3, 39)])
```

```
Index(['2017-05-16 12:00:00', '2017-05-25 12:00:00', '2017-06-02 12:00:
00',
       '2017-06-03 12:00:00', '2017-06-05 12:00:00', '2017-06-06 12:00:
00',
       '2017-06-08 12:00:00', '2017-06-09 12:00:00', '2017-06-10 12:00:
00',
       '2017-08-25 12:00:00', '2017-08-26 12:00:00', '2017-08-29 12:00:
00',
       '2017-07-05 12:00:00', '2017-06-16 12:00:00', '2017-06-25 12:00:
00',
       '2017-07-01 12:00:00', '2017-07-02 12:00:00', '2017-06-24 12:00:
00',
       '2017-07-04 12:00:00'],
      dtype='object')
```

In [249]:

```
count = 0
for group in full_df.groupby(['cultivar','column','range']).groups:
    print(group)
    count += 1
    if count>5:
        break
```

```
(6000000207, 3, 39)
(6000000207, 9, 23)
(6000000208, 14, 26)
(6000000208, 15, 30)
(6000000209, 4, 39)
(6000000209, 13, 23)
```

In [220]:

```
# find a subset dataframe that contains the locations of a single cultivar in a sin
gle location in the field
grouped = full_df.groupby(['cultivar','column','range'])
for name,group in grouped:
    print(name)
    print(group)
    break
```

```
(6000000207, 3, 39)
                     canopy_height  column    cultivar                    
date  \
2017-05-16 12:00:00           22.0       3  6000000207  2017-05-16 12:0
0:00
2017-05-25 12:00:00           48.0       3  6000000207  2017-05-25 12:0
0:00
2017-06-02 12:00:00           89.0       3  6000000207  2017-06-02 12:0
0:00
2017-06-03 12:00:00           95.0       3  6000000207  2017-06-03 12:0
0:00
2017-06-05 12:00:00          113.0       3  6000000207  2017-06-05 12:0
0:00
2017-06-06 12:00:00          116.0       3  6000000207  2017-06-06 12:0
0:00
2017-06-08 12:00:00          132.0       3  6000000207  2017-06-08 12:0
0:00
2017-06-09 12:00:00          141.0       3  6000000207  2017-06-09 12:0
0:00
2017-06-10 12:00:00          150.0       3  6000000207  2017-06-10 12:0
0:00
2017-08-25 12:00:00          317.0       3  6000000207  2017-08-25 12:0
0:00
2017-08-26 12:00:00          317.0       3  6000000207  2017-08-26 12:0
0:00
2017-08-29 12:00:00          318.0       3  6000000207  2017-08-29 12:0
0:00
2017-07-05 12:00:00          268.0       3  6000000207  2017-07-05 12:0
0:00
2017-06-16 12:00:00          190.0       3  6000000207  2017-06-16 12:0
0:00
2017-06-25 12:00:00          232.0       3  6000000207  2017-06-25 12:0
0:00
2017-07-01 12:00:00          252.0       3  6000000207  2017-07-01 12:0
0:00
2017-07-02 12:00:00          257.0       3  6000000207  2017-07-02 12:0
0:00
2017-06-24 12:00:00          229.0       3  6000000207  2017-06-24 12:0
0:00
2017-07-04 12:00:00          265.0       3  6000000207  2017-07-04 12:0
0:00

                     leaf_angle_alpha  leaf_angle_beta  leaf_angle_chi
\
2017-05-16 12:00:00          3.029223         1.961442        1.870532
2017-05-25 12:00:00          2.109788         1.673649        1.710402
2017-06-02 12:00:00          2.447258         1.713407        1.837392
2017-06-03 12:00:00          3.109602         1.913697        1.942567
2017-06-05 12:00:00          2.976765         1.894488        1.910338
2017-06-06 12:00:00          2.805701         1.866598        1.825539
2017-06-08 12:00:00          3.269036         1.791071        2.108108
2017-06-09 12:00:00          2.506393         1.684057        1.881935
2017-06-10 12:00:00          3.163247         1.875412        1.972441
2017-08-25 12:00:00          1.934727         1.635415        1.670653
2017-08-26 12:00:00          1.749690         1.547534        1.631517
2017-08-29 12:00:00          2.627726         2.670668        1.454754
2017-07-05 12:00:00          2.208545         1.676181        1.765525
```

```
2017-06-16 12:00:00          2.402276          1.695992          1.830182
2017-06-25 12:00:00          2.051962          1.663227          1.708243
2017-07-01 12:00:00          2.324980          1.635286          1.880807
2017-07-02 12:00:00          4.298827          2.328273          2.044120
2017-06-24 12:00:00          3.086483          2.361568          1.665006
2017-07-04 12:00:00          4.686466          2.249569          2.225622

                     leaf_angle_mean  range  season
2017-05-16 12:00:00         0.420787     39       4
2017-05-25 12:00:00         0.461486     39       4
2017-06-02 12:00:00         0.431054     39       4
2017-06-03 12:00:00         0.403784     39       4
2017-06-05 12:00:00         0.409748     39       4
2017-06-06 12:00:00         0.435253     39       4
2017-06-08 12:00:00         0.383240     39       4
2017-06-09 12:00:00         0.432157     39       4
2017-06-10 12:00:00         0.410376     39       4
2017-08-25 12:00:00         0.458132     39       4
2017-08-26 12:00:00         0.469848     39       4
2017-08-29 12:00:00         0.489575     39       4
2017-07-05 12:00:00         0.446889     39       4
2017-06-16 12:00:00         0.437703     39       4
2017-06-25 12:00:00         0.456029     39       4
2017-07-01 12:00:00         0.425270     39       4
2017-07-02 12:00:00         0.378729     39       4
2017-06-24 12:00:00         0.455954     39       4
2017-07-04 12:00:00         0.343710     39       4
```

Fit Models to the Season 4 extraction

In [2]:

```
import sklearn
import pandas as pd
```

In [253]:

```
# paste code from another notebook that uses 'cdf' as the source dataframe.  It
# is easier to just copy to that same variable name
cdf = full_df
```

In [254]:

```
cdf.head()
```

Out[254]:

	canopy_height	column	cultivar	date	leaf_angle_alpha	leaf_angle_beta	leaf_an
2017-05-13 12:00:00	15.0	2	6000000836	2017-05-13 12:00:00	2.695956	1.977380	1.'
2017-05-13 12:00:00	15.0	15	6000000462	2017-05-13 12:00:00	3.265980	2.018623	1.!
2017-05-13 12:00:00	19.0	2	6000000751	2017-05-13 12:00:00	2.159610	1.809209	1.(
2017-05-13 12:00:00	13.0	4	6000000916	2017-05-13 12:00:00	3.042180	2.198751	1.'
2017-05-15 12:00:00	17.0	2	6000000976	2017-05-15 12:00:00	2.305345	1.872028	1.(

In [255]:

```
train_df = cdf[['cultivar','day_offset','range','column','leaf_angle_alpha','leaf_a
ngle_beta','leaf_angle_chi','leaf_angle_mean']]
target_df = cdf['canopy_height']
```

In [256]:

```
X_train = train_df.values
y_train = target_df.values
print(X_train.shape)
print(y_train.shape)
```

```
(9441, 8)
(9441,)
```

In [ ]:

In [265]:

```
from sklearn.tree import DecisionTreeRegressor
from sklearn.linear_model import LinearRegression
from sklearn import svm
from sklearn.ensemble import GradientBoostingRegressor

tree = DecisionTreeRegressor(max_depth=8).fit(X_train, y_train)
linear_reg = LinearRegression().fit(X_train, y_train)
#svm_mod = svm.SVR().fit(X_train, y_train)
gbr_mod = GradientBoostingRegressor(n_estimators=100, learning_rate=0.1, max_depth=
8, random_state=0, loss='ls').fit(X_train, y_train)

pred_tree = tree.predict(X_train)
pred_lr = linear_reg.predict(X_train)
#pred_svm = svm_mod.predict(X_train)
pred_gbr = gbr_mod.predict(X_train)
```

In [266]:

```
cdf['decision_tree'] = pred_tree
cdf['linearRegression'] = pred_lr
#cdf['svm'] = pred_svm
cdf['gboost'] = pred_gbr
cdf.head()
```

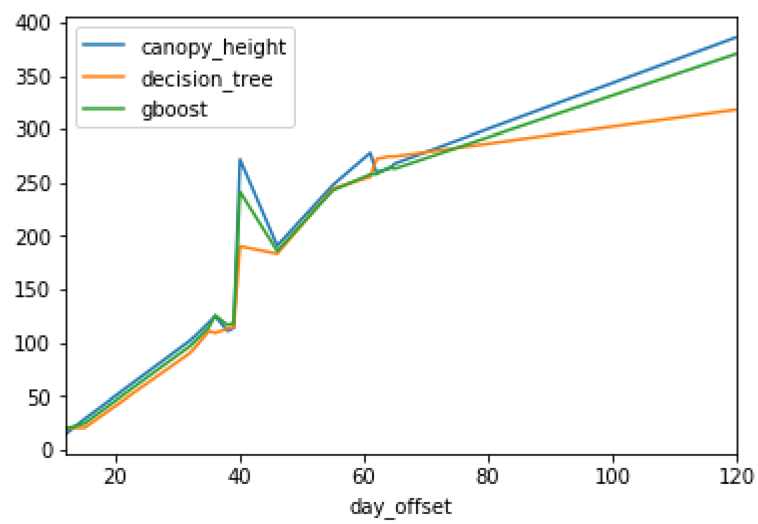
Out[266]:

	canopy_height	column	cultivar	date	leaf_angle_alpha	leaf_angle_beta	leaf_an
2017-05-13 12:00:00	15.0	2	6000000836	2017-05-13 12:00:00	2.695956	1.977380	1.
2017-05-13 12:00:00	15.0	15	6000000462	2017-05-13 12:00:00	3.265980	2.018623	1.
2017-05-13 12:00:00	19.0	2	6000000751	2017-05-13 12:00:00	2.159610	1.809209	1.
2017-05-13 12:00:00	13.0	4	6000000916	2017-05-13 12:00:00	3.042180	2.198751	1.
2017-05-15 12:00:00	17.0	2	6000000976	2017-05-15 12:00:00	2.305345	1.872028	1.

In [267]:

```
%matplotlib inline
import matplotlib.pyplot as plt

def plot_cultivar(fulldf,cultivar):
    df = fulldf.loc[fulldf['cultivar'] == cultivar]
    minCol = df['column'].min()
    df = df.loc[df['column']==minCol]
    #print(df.shape)
    df = df[['day_offset','canopy_height','decision_tree','gboost']]
    df = df.set_index('day_offset')
    df = df.sort_index()
    print(df)
    df.plot()

#plot_cultivar(cdf,'PI145619')
plot_cultivar(cdf,6000000836)
```

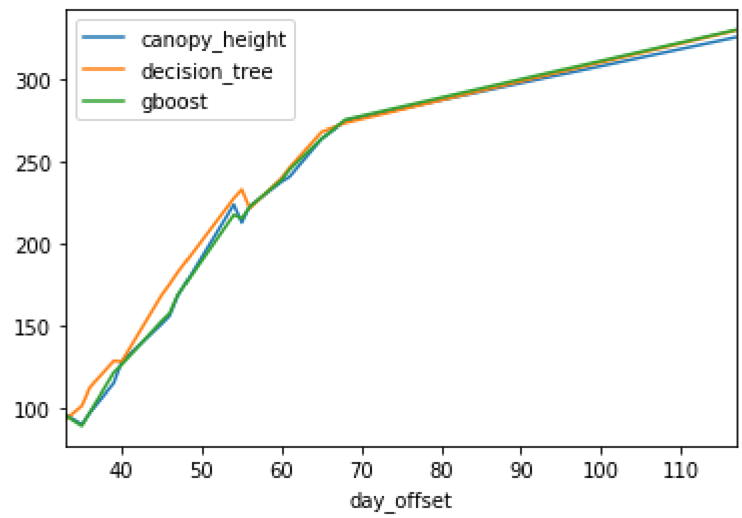
```
            canopy_height  decision_tree      gboost
day_offset
12                   15.0      20.684211   19.914282
15                   29.0      20.684211   24.810587
32                  102.0      90.363636   96.840969
35                  119.0     110.971963  114.542491
36                  125.0     109.250000  125.781571
38                  111.0     113.250000  116.642920
39                  114.0     114.866667  118.596735
40                  272.0     190.500000  241.614416
46                  191.0     183.476190  186.047126
55                  248.0     244.583333  242.984222
61                  278.0     255.428571  257.851301
62                  260.0     272.200000  258.050972
64                  263.0     274.647887  264.090317
65                  268.0     274.647887  263.217710
120                 386.0     318.171875  370.444316
```



In [268]:

```
plot_cultivar(cdf,6000000462)
```

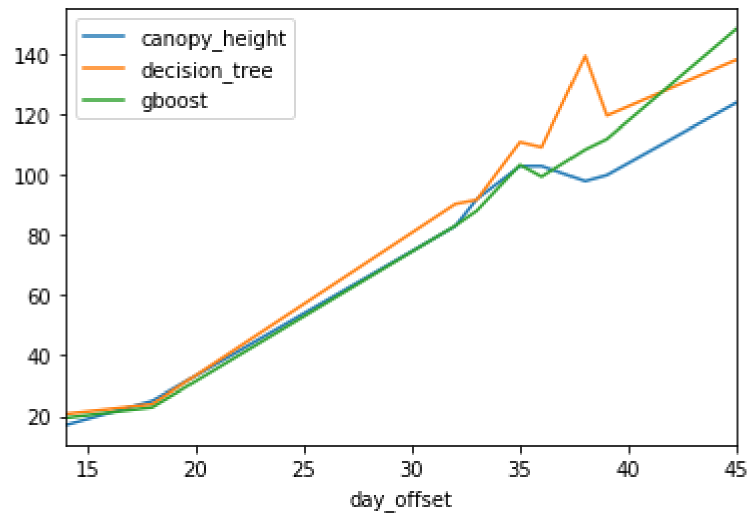
day_offset	canopy_height	decision_tree	gboost
33	96.0	93.184211	95.295526
35	90.0	101.326087	89.041657
36	97.0	112.330508	97.400502
39	115.0	128.512821	121.455541
40	128.0	128.145455	126.195282
45	151.0	168.659722	152.864520
46	156.0	175.333333	157.547256
47	168.0	182.545455	168.697935
54	224.0	227.835294	217.687636
55	213.0	233.208791	215.623566
56	223.0	221.681818	222.594397
60	238.0	240.298013	239.141691
61	241.0	246.661417	245.439149
65	264.0	268.322917	264.207241
68	275.0	273.623229	275.614637
117	326.0	330.142857	330.534632



In [269]:

```
plot_cultivar(cdf,6000000976)
```

```
            canopy_height  decision_tree      gboost
day_offset
14                   17.0      20.684211   19.387769
18                   25.0      23.906250   22.868977
32                   83.0      90.363636   83.121168
33                   92.0      91.794872   88.127969
35                  103.0     110.971963  103.402695
36                  103.0     109.250000   99.482699
38                   98.0     139.500000  108.437526
39                  100.0     119.666667  111.939874
45                  124.0     138.250000  148.556495
```



Try to visualize the results across the field by finding the delta at each location between the observed and the model output. Try to use Vega or VegaLite. Checkout the native integration explained here: [https://github.com/jupyterlab/jupyterlab/blob/master/examples/vega/vega-extension.ipynb (https://github.com/jupyterlab/jupyterlab/blob/master/examples/vega/vega-extension.ipynb)](https://github.com/jupyterlab/jupyterlab/blob/master/examples/vega/vega-extension.ipynb)

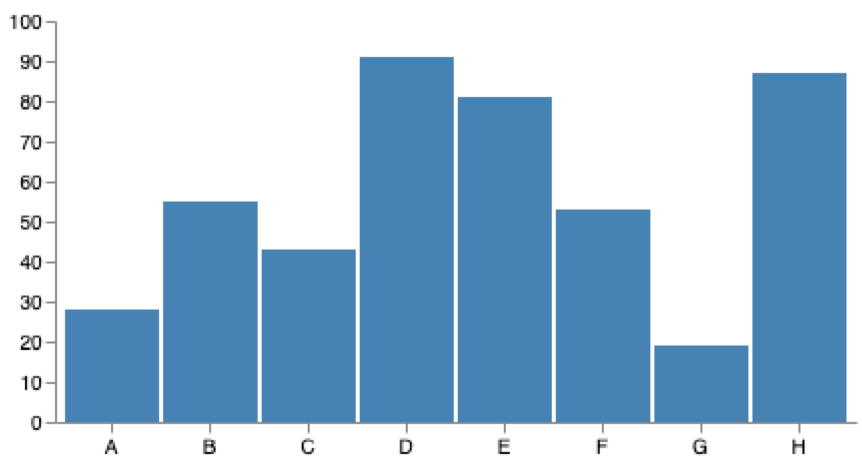
In [85]:

```
from IPython.display import display
import pandas as pd

def Vega(spec):
    bundle = {}
    bundle['application/vnd.vega.v4+json'] = spec
    display(bundle, raw=True)

def VegaLite(spec):
    bundle = {}
    bundle['application/vnd.vegalite.v2+json'] = spec
    display(bundle, raw=True)
```

In [87]:

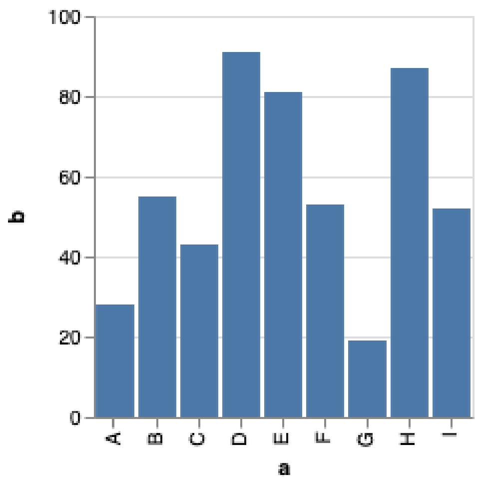
```
Vega({
  "$schema": "https://vega.github.io/schema/vega/v3.0.json",
  "width": 400,
  "height": 200,
  "padding": 5,

  "data": [
    {
      "name": "table",
      "values": [
        {"category": "A", "amount": 28},
        {"category": "B", "amount": 55},
        {"category": "C", "amount": 43},
        {"category": "D", "amount": 91},
        {"category": "E", "amount": 81},
        {"category": "F", "amount": 53},
        {"category": "G", "amount": 19},
        {"category": "H", "amount": 87}
      ]
    }
  ],

  "signals": [
    {
      "name": "tooltip",
      "value": {},
      "on": [
        {"events": "rect:mouseover", "update": "datum"},
        {"events": "rect:mouseout",  "update": "{}"}
      ]
    }
  ],

  "scales": [
    {
      "name": "xscale",
      "type": "band",
      "domain": {"data": "table", "field": "category"},
      "range": "width",
      "padding": 0.05,
      "round": True
    },
    {
      "name": "yscale",
      "domain": {"data": "table", "field": "amount"},
      "nice": True,
      "range": "height"
    }
  ],

  "axes": [
    { "orient": "bottom", "scale": "xscale" },
    { "orient": "left", "scale": "yscale" }
  ],
```

```
  "marks": [
    {
      "type": "rect",
      "from": {"data":"table"},
      "encode": {
        "enter": {
          "x": {"scale": "xscale", "field": "category"},
          "width": {"scale": "xscale", "band": 1},
          "y": {"scale": "yscale", "field": "amount"},
          "y2": {"scale": "yscale", "value": 0}
        },
        "update": {
          "fill": {"value": "steelblue"}
              },
        "hover": {
          "fill": {"value": "red"}
        }
      }
    },
    {
      "type": "text",
      "encode": {
        "enter": {
          "align": {"value": "center"},
          "baseline": {"value": "bottom"},
          "fill": {"value": "#333"}
        },
        "update": {
          "x": {"scale": "xscale", "signal": "tooltip.category", "band": 0.5},
          "y": {"scale": "yscale", "signal": "tooltip.amount", "offset": -2},
          "text": {"signal": "tooltip.amount"},
          "fillOpacity": [
            {"test": "datum === tooltip", "value": 0},
            {"value": 1}
          ]
        }
      }
    }
  ]
})
```



In [86]:

```
VegaLite({
  "$schema": "https://vega.github.io/schema/vega-lite/v2.json",
  "description": "A simple bar chart with embedded data.",
  "data": {
    "values": [
      {"a": "A","b": 28}, {"a": "B","b": 55}, {"a": "C","b": 43},
      {"a": "D","b": 91}, {"a": "E","b": 81}, {"a": "F","b": 53},
      {"a": "G","b": 19}, {"a": "H","b": 87}, {"a": "I","b": 52}
    ]
  },
  "mark": "bar",
  "encoding": {
    "x": {"field": "a", "type": "ordinal"},
    "y": {"field": "b", "type": "quantitative"}
  }
})
```



In [92]:

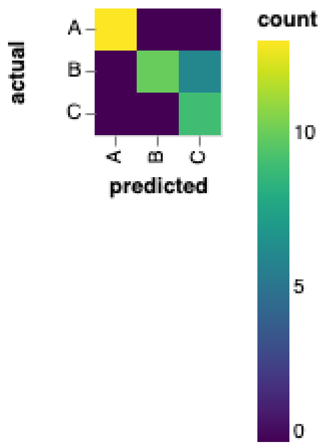
```
VegaLite({
  "$schema": "https://vega.github.io/schema/vega-lite/v4.json",
  "data": {"url": "data/movies.json"},
  "spacing": 15,
  "bounds": "flush",
  "vconcat": [{
    "mark": "bar",
    "height": 60,
    "encoding": {
      "x": {
        "bin": True,
        "field": "IMDB_Rating",
        "type": "quantitative",
        "axis": None
      },
      "y": {
        "aggregate": "count",
        "type": "quantitative",
        "scale": {
          "domain": [0,1000]
        },
        "title": ""
      }
    }
  }, {
    "spacing": 15,
    "bounds": "flush",
    "hconcat": [{
      "mark": "rect",
      "encoding": {
        "x": {
          "bin": True,
          "field": "IMDB_Rating",
          "type": "quantitative"
        },
        "y": {
          "bin": True,
          "field": "Rotten_Tomatoes_Rating",
          "type": "quantitative"
        },
        "color": {
          "aggregate": "count",
          "type": "quantitative"
        }
      }
    }, {
      "mark": "bar",
      "width": 60,
      "encoding": {
        "y": {
          "bin": True,
          "field": "Rotten_Tomatoes_Rating",
          "type": "quantitative",
          "axis": None
        },
```

```
          "x": {
            "aggregate": "count",
            "type": "quantitative",
            "scale": {
              "domain": [0,1000]
            },
            "title": ""
          }
        }
      }]
    }],
    "config": {
      "view": {
        "stroke": "transparent"
      }
    }
  })
```

In [94]:

```
VegaLite({
  "data": {
    "values": [
      {"actual": "A", "predicted": "A", "count": 13},
      {"actual": "A", "predicted": "B", "count": 0},
      {"actual": "A", "predicted": "C", "count": 0},
      {"actual": "B", "predicted": "A", "count": 0},
      {"actual": "B", "predicted": "B", "count": 10},
      {"actual": "B", "predicted": "C", "count": 6},
      {"actual": "C", "predicted": "A", "count": 0},
      {"actual": "C", "predicted": "B", "count": 0},
      {"actual": "C", "predicted": "C", "count": 9}
    ]
  },
  "selection": {
    "highlight": {"type": "single"}
  },
  "mark": {"type": "rect", "strokeWidth": 2},
  "encoding": {
    "y": {
      "field": "actual",
      "type": "nominal"
    },
    "x": {
      "field": "predicted",
      "type": "nominal"
    },
    "fill": {
      "field": "count",
      "type": "quantitative"
    },
    "stroke": {
      "condition": {"test": {"and": [{"selection": "highlight"}, "length(data(\"hig
hlight_store\"))"]}, "value": "black"},
      "value": None
    },
    "opacity": {
      "condition": {"selection": "highlight", "value": 1},
      "value": 0.5
    },
    "order": {
      "condition": {"selection": "highlight", "value": 1},
      "value": 0
    }
  },
  "config": {
    "scale": {
      "bandPaddingInner": 0,
      "bandPaddingOuter": 0
    },
    "view": {"step": 40},
    "range": {
      "ramp": {
        "scheme": "yellowgreenblue"
      }
```

```
    },
    "axis": {
      "domain": False,
      "zindex": 0
    }
  }
}
)
```



Train a model for each cultivar in its location.

Do this by using groupby in pandas to create a separate group for each cultivar at a particular location. Then we will build an retain a set of group-specific models,

In [ ]:

```
gbr_models = {}
predictions = {}
count = 0
grouped = full_df.groupby(['cultivar','column','range'])
for name,group in grouped:
    #print(name)
    # pick the features to use for training
    train_df = group[['cultivar','day_offset','range','column','leaf_angle_alpha',
'leaf_angle_beta','leaf_angle_chi','leaf_angle_mean']]
    # identify the 'target' feature to try to predict
    target_df = group['canopy_height']
    X_train = train_df.values
    y_train = target_df.values
    # train a model for this cultivar in this location and store the trained model
 in a dictionary
    gbr_models[name] = GradientBoostingRegressor(n_estimators=100, learning_rate=0.
1, max_depth=8, random_state=0, loss='ls').fit(X_train, y_train)
    gbr_pred = gbr_models[name].predict(X_train)
    count += 1
    # add the model results back into the dataframe so we can plot the actual and p
redicted against all the indepedent variables
    train_df['gboost'] = gbr_pred
    #put the actual target value back in the dataframe so we can plot results
    train_df['canopy_height'] = target_df
    # store the predicted results in the same dictionary organization and the train
ed models
    predictions[name] = train_df
print('finished generating',count,'models')
```

In [300]:

```
# look at the output dataframe of one cultivar,column,range tuple
predictions[(6000000207, 3, 39)]
```

Out[300]:

	cultivar	day_offset	range	column	leaf_angle_alpha	leaf_angle_beta	leaf_angle_chi
2017-05-16 12:00:00	6000000207	15	39	3	3.029223	1.961442	1.870532
2017-05-25 12:00:00	6000000207	24	39	3	2.109788	1.673649	1.710402
2017-06-02 12:00:00	6000000207	32	39	3	2.447258	1.713407	1.837392
2017-06-03 12:00:00	6000000207	33	39	3	3.109602	1.913697	1.942567
2017-06-05 12:00:00	6000000207	35	39	3	2.976765	1.894488	1.910338
2017-06-06 12:00:00	6000000207	36	39	3	2.805701	1.866598	1.825539
2017-06-08 12:00:00	6000000207	38	39	3	3.269036	1.791071	2.108108
2017-06-09 12:00:00	6000000207	39	39	3	2.506393	1.684057	1.881935
2017-06-10 12:00:00	6000000207	40	39	3	3.163247	1.875412	1.972441
2017-08-25 12:00:00	6000000207	116	39	3	1.934727	1.635415	1.670653
2017-08-26 12:00:00	6000000207	117	39	3	1.749690	1.547534	1.631517
2017-08-29 12:00:00	6000000207	120	39	3	2.627726	2.670668	1.454754
2017-07-05 12:00:00	6000000207	65	39	3	2.208545	1.676181	1.765525
2017-06-16 12:00:00	6000000207	46	39	3	2.402276	1.695992	1.830182
2017-06-25 12:00:00	6000000207	55	39	3	2.051962	1.663227	1.708243

	cultivar	day_offset	range	column	leaf_angle_alpha	leaf_angle_beta	leaf_angle_chi
2017-07-01 12:00:00	6000000207	61	39	3	2.324980	1.635286	1.880807
2017-07-02 12:00:00	6000000207	62	39	3	4.298827	2.328273	2.044120
2017-06-24 12:00:00	6000000207	54	39	3	3.086483	2.361568	1.665006
2017-07-04 12:00:00	6000000207	64	39	3	4.686466	2.249569	2.225622

Define a variation of the plotting routine that retrieves values from the trained model's predictions and compares them to the original observed values.

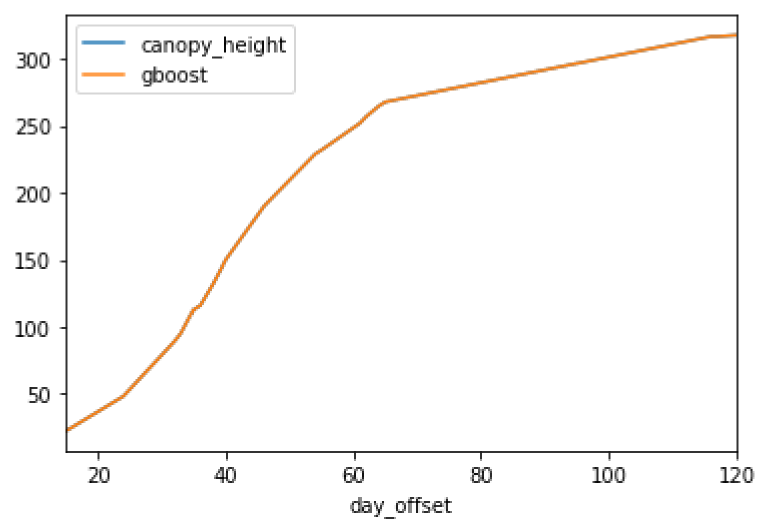
In [290]:

```
def plot_specific_cultivar(cultivar,col,rng):
    df = predictions[(cultivar,col,rng)]
    minCol = df['column'].min()
    df = df.loc[df['column']==minCol]
    print(df.shape)
    df = df[['day_offset','canopy_height','gboost']]
    df = df.set_index('day_offset')
    df = df.sort_index()
    print(df)
    df.plot()
```

In [291]:

```
plot_specific_cultivar(6000000207, 3, 39)
```

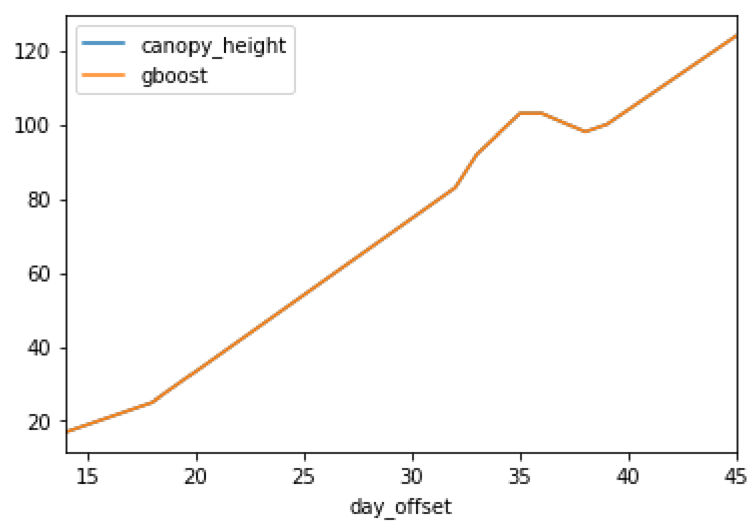
```
(19, 10)
            canopy_height      gboost
day_offset
15                   22.0   22.004380
24                   48.0   48.003689
32                   89.0   89.002743
33                   95.0   95.002346
35                  113.0  113.002056
36                  116.0  116.001794
38                  132.0  132.001485
39                  141.0  141.001287
40                  150.0  150.000832
46                  190.0  189.999918
54                  229.0  228.999029
55                  232.0  231.998696
61                  252.0  251.998352
62                  257.0  256.998162
64                  265.0  264.998007
65                  268.0  267.997617
116                 317.0  316.996744
117                 317.0  316.996744
120                 318.0  317.996118
```



In [301]:

```
plot_specific_cultivar(6000000976,2,45)
```

```
(9, 10)
            canopy_height      gboost
day_offset
14                   17.0   17.001946
18                   25.0   25.001336
32                   83.0   83.000069
33                   92.0   91.999766
35                  103.0  102.999240
36                  103.0  102.999240
38                   98.0   97.999908
39                  100.0   99.999590
45                  124.0  123.998905
cultivar = 0.0
day_offset = 0.9816231179970161
range = 0.0
column = 0.0
leaf_angle_alpha = 0.0069385988263879405
leaf_angle_beta = 0.0021028904217576527
leaf_angle_chi = 0.007547074015750632
leaf_angle_mean = 0.0017883187390877555
```



the above plots show that a gradient boost model can precisely fit the observed data when trained on only the particular cultivar and location measurements. This isn't too much of a surprise. It shows that a single model for the whole field can't match as well (at least when using the cultivar as an integer variable). Ideally, we should have one-hot encoded the cultivar as a categorical variable.

How to find the feature importances. This is an output of the trained model. Lets look at one before we add it to the plot

In [293]:

```
feature_names = ['cultivar','day_offset','range','column','leaf_angle_alpha','leaf_
angle_beta','leaf_angle_chi','leaf_angle_mean']
for name, importance in zip(feature_names, gbr_models[(6000000976,2,45)].feature_im
portances_):
    print(name, "=", importance)
```

```
cultivar = 0.0
day_offset = 0.9816231179970161
range = 0.0
column = 0.0
leaf_angle_alpha = 0.0069385988263879405
leaf_angle_beta = 0.0021028904217576527
leaf_angle_chi = 0.007547074015750632
leaf_angle_mean = 0.0017883187390877555
```

Unsurprisingly, the day, which represents how far into the growing season we are, is by far (98%) the most driving factor of calculating the model result.

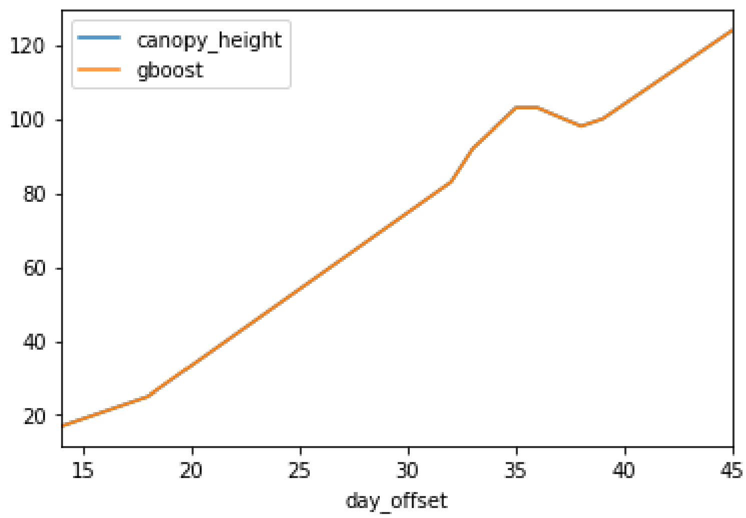
In [295]:

```
def plot_specific_cultivar(cultivar,col,rng):
    feature_names = ['cultivar','day_offset','range','column','leaf_angle_alpha','l
eaf_angle_beta','leaf_angle_chi','leaf_angle_mean']
    df = predictions[(cultivar,col,rng)]
    minCol = df['column'].min()
    df = df.loc[df['column']==minCol]
    print(df.shape)
    df = df[['day_offset','canopy_height','gboost']]
    df = df.set_index('day_offset')
    df = df.sort_index()
    print(df)
    df.plot()
    for name, importance in zip(feature_names, gbr_models[(cultivar,col,rng)].featu
re_importances_):
        print(name, "=", importance)
```

In [296]:

```
plot_specific_cultivar(6000000976,2,45)
```

```
(9, 10)
            canopy_height      gboost
day_offset
14                   17.0   17.001946
18                   25.0   25.001336
32                   83.0   83.000069
33                   92.0   91.999766
35                  103.0  102.999240
36                  103.0  102.999240
38                   98.0   97.999908
39                  100.0   99.999590
45                  124.0  123.998905
cultivar = 0.0
day_offset = 0.9816231179970161
range = 0.0
column = 0.0
leaf_angle_alpha = 0.0069385988263879405
leaf_angle_beta = 0.0021028904217576527
leaf_angle_chi = 0.007547074015750632
leaf_angle_mean = 0.0017883187390877555
```



In [46]:

```
full_df.columns
```

Out[46]:

```
Index(['canopy_height', 'column', 'cultivar', 'date', 'leaf_angle_alph
a',
       'leaf_angle_beta', 'leaf_angle_chi', 'leaf_angle_mean', 'range',
       'season', 'day_offset'],
      dtype='object')
```

test how to convert column to categorical

In [ ]:

```
# make sure the cultivar is a categorical type variable
full_df = full_df[['cultivar','column','range','date','season','day_offset','leaf_a
ngle_alpha','leaf_angle_beta','leaf_angle_chi','leaf_angle_mean']]
full_df['cultivar'] = pd.Categorical(full_df['cultivar'])
full_df.dtypes
```

In [308]:

```
train = full_df
for col in train.dtypes[train.dtypes == 'category'].index:
    for_dummy = train.pop(col)
    train = pd.concat([train, pd.get_dummies(for_dummy, prefix=col)], axis=1)
```

train-test splitting on time sequence data?

Sci-kit learn includes a special TimeSeriesSplit operation that takes more of the sequence for training each time, and pulls the 'immediately after training' value for the testing prediction. This will train on a small subset of the input originally and eventually use most of the input for training. Overall, it will yield an accuracy representative of querying at any time during the sequence.

The problem of using this on the separated cultivar-range-column models is that very few datapoints are available for training. If we further reduce the number of points through train/test split, accuracy could suffer. However, it is representative of the data available at each point during the season, so this is realistic. Let's modify the training above to use a train/test split. At the same time, lets one-hot encode the cultivars.

In [309]:

```
train.columns
```

Out[309]:

```
Index(['column', 'range', 'date', 'season', 'day_offset', 'leaf_angle_a
lpha',
       'leaf_angle_beta', 'leaf_angle_chi', 'leaf_angle_mean',
       'cultivar_6000000207',
       ...
       'cultivar_6000001029', 'cultivar_6000001054', 'cultivar_60000010
55',
       'cultivar_6000001056', 'cultivar_6000001057', 'cultivar_60000010
59',
       'cultivar_6000001060', 'cultivar_6000001061', 'cultivar_60000010
62',
       'cultivar_6000001063'],
      dtype='object', length=360)
```

In [84]:

```
from sklearn.model_selection import TimeSeriesSplit
from sklearn.model_selection import train_test_split
from sklearn.model_selection import ShuffleSplit

from sklearn.ensemble import GradientBoostingRegressor
#warnings.warn(NSPLIT_WARNING, FutureWarning)

gbr_models2 = {}
predictions2 = {}
count = 0
grouped2 = full_df.groupby(['cultivar','column','range'])
for name,group in grouped2:
    #print(name)
    # pick the features to use for training
    train_df = group[['cultivar','day_offset','range','column','leaf_angle_alpha',
'leaf_angle_beta','leaf_angle_chi','leaf_angle_mean']]
    train_df['cultivar'] = pd.Categorical(train_df['cultivar'])
    # identify the 'target' feature to try to predict
    target_df = group['canopy_height']
    if len(train_df) > 20:
        X = train_df.values
        y = target_df.values
        count += 1
        print('shape X:',X.shape,' y:',y.shape)
        tss= TimeSeriesSplit(n_splits=2)
        #tss= ShuffleSplit()
        print("X_train:",X_train,"y_train:",y_train)
        print("X_test:",X_test,"y_test:",y_test)
        for train_index, test_index in tss.split(X):
            print(train_index,test_index)
            X_train, X_test = X[train_index], X[test_index]
            y_train, y_test = y[train_index], y[test_index]

            # train a model for this cultivar in this location and store the traine
d model in a dictionary
            gbr_models2[name] = GradientBoostingRegressor(n_estimators=100, learnin
g_rate=0.1, max_depth=8, random_state=0, loss='ls').fit(X_train, y_train)
            gbr_pred = gbr_models2[name].predict(X_test)
            print('predictions:',gbr_pred)

            predictions2[name] = gbr_models2[name].score(X_test,y_test)
            #print('training set score: {:.2f}'.format(gbr_models2[name].score(X_tr
ain,y_train)))
            #print('test set score: {:.2f}'.format(gbr_models2[name].score(X_test,y
_test)))
    if count > 2:
        break
print('finished generating',count,'models')
```

```
/Users/curtislisle/anaconda3/lib/python3.7/site-packages/ipykernel_laun
cher.py:16: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-d
ocs/stable/indexing.html#indexing-view-versus-copy
  app.launch_new_instance()
```

```
shape X: (21, 8)  y: (21,)
X_train: [[6000000464 15.0 51 3 3.25326410587 2.15918306701 1.843802578
19
  0.414221305212]
 [6000000464 18.0 51 3 2.94826514793 2.01419013348 1.8075966298400004
  0.431598041787]
 [6000000464 23.0 51 3 1.7511163258900002 1.66705407447 1.54119024613
  0.494613883754]
 [6000000464 24.0 51 3 2.19170262675 1.8679376954499998 1.62562900495
  0.469079643023]
 [6000000464 32.0 51 3 3.5928799038999997 2.1606193934299998 1.92831465
53
  0.40532649796400005]
 [6000000464 34.0 51 3 3.20477135316 2.03687477467 1.88394704345
  0.41585510941200005]
 [6000000464 36.0 51 3 3.40775289944 2.1041825957299998 1.90204810526
  0.41438958781199997]
 [6000000464 38.0 51 3 4.2124949121599995 2.25164810824
  2.0604689307900004 0.38107418415399996]
 [6000000464 39.0 51 3 3.23512994709 1.99929908999 1.9224658635
  0.412805160034]
 [6000000464 40.0 51 3 2.77639680201 1.85075021058 1.8885756006299999
  0.41510408940300003]
 [6000000464 41.0 51 3 3.0595421391400004 1.86790320508 1.95027669178
  0.412133818686]
 [6000000464 44.0 51 3 3.24247758462 1.93164125477 1.97913432129
  0.402507233118]
 [6000000464 56.0 51 3 2.47638200943 1.7215131018099998
  1.8212637867900001 0.44100594719999997]
 [6000000464 47.0 51 3 3.1375167635500003 1.8127001163299998
  2.03955542392 0.397050502077]
 [6000000464 55.0 51 3 2.66453792043 1.69844979087 1.9700587219799999
  0.40600389079000004]
 [6000000464 57.0 51 3 3.4083684372099996 1.9450404471400002
  2.04808441975 0.38395380492799996]
 [6000000464 58.0 51 3 3.98181884753 1.9975937661099996 2.20964378594
  0.35414748575800004]] y_train: [ 16.  18.  31.  37.  70.  89.  97. 12
0. 125. 133. 138. 157. 241. 183.
 238. 248. 252.]
X_test: [[6000000464 60.0 51 3 1.909342715 1.73478673058 1.583432549740
0001
  0.485911712492]
 [6000000464 61.0 51 3 2.10972041331 1.7964194816599999
  1.6274107507299997 0.474432664147]
 [6000000464 62.0 51 3 3.20739383324 1.84925654336 2.0636416843400003
  0.380860236285]
 [6000000464 54.0 51 3 2.9111085015400002 1.63727401815 2.13988248196
  0.390122364735]] y_test: [261. 264. 269. 225.]
[0 1 2 3 4 5 6] [ 7  8  9 10 11 12 13]
predictions: [114.25182053 121.41467107 122.00348456  69.7722769   69.7
722769
  80.27396664  78.52685462]
[ 0  1  2  3  4  5  6  7  8  9 10 11 12 13] [14 15 16 17 18 19 20]
predictions: [291.99650718 265.07232983 265.07232983 265.07232983 291.9
9650718
 152.02158302 265.07232983]
shape X: (21, 8)  y: (21,)
```

```
X_train: [[6000000228 19.0 40 14 2.7906560083 2.04413151183 1.735344624
75
  0.441877991649]
 [6000000228 24.0 40 14 2.2055647624900003 1.80144033521
  1.6796961337799998 0.45895432310500006]
 [6000000228 32.0 40 14 3.8398695568699996 2.16910761412 2.00743186378
  0.390038314176]
 [6000000228 33.0 40 14 4.337001611619999 2.4282182202300002 1.99519581
73
  0.384151285353]
 [6000000228 35.0 40 14 3.5995654499 2.0569006180000002 2.01570915454
  0.386505583713]
 [6000000228 36.0 40 14 4.7383464482 2.88328426672 1.8752139832199999
  0.40056777441200003]
 [6000000228 38.0 40 14 4.027962904080001 1.95711108337 2.23322124813
  0.364568978107]
 [6000000228 39.0 40 14 3.62070081191 2.00928263662 2.03557535339
  0.397134930884]
 [6000000228 40.0 40 14 3.68200095734 1.9881575051299998 2.07144948629
  0.391278924943]
 [6000000228 45.0 40 14 3.31281399999 1.9534903563 1.96618468163
  0.409954718243]
 [6000000228 116.0 40 14 1.2696030752 1.32525609604 1.51957709354
  0.50599040977]
 [6000000228 117.0 40 14 1.1736358784899998 1.29732833004 1.46559807406
  0.51802306022]
 [6000000228 65.0 40 14 2.38609182436 1.70966789917 1.8144001487
  0.438516349671]
 [6000000228 46.0 40 14 2.9035771391100003 1.9054704226499999
  1.84926019993 0.435476032693]] y_train: [ 25.  44.  80.  82. 109. 11
4. 130. 142. 150. 180. 357. 356. 292. 186.]
X_test: [[6000000228 57.0 40 14 2.58225875657 1.74546468018 1.842998991
51
  0.43836018683300004]
 [6000000228 58.0 40 14 2.6561213916499997 1.7630144205900002
  1.8600430020900003 0.43447565110200004]
 [6000000228 60.0 40 14 2.7580258067699996 1.8132877779900003
  1.8630897544999998 0.433064189793]
 [6000000228 61.0 40 14 2.8324994504000003 1.8084019155700002
  1.89243722526 0.43016229920800003]
 [6000000228 62.0 40 14 2.59080385368 1.7427842988099997
  1.8640930662900002 0.431069786489]
 [6000000228 54.0 40 14 3.91489111054 2.25602768094 1.94386278336
  0.4089322439]
 [6000000228 68.0 40 14 2.59954237727 1.85508884777 1.7725285032900002
  0.444793178685]] y_test: [256. 257. 266. 275. 278. 215. 291.]
[0 1 2 3 4 5 6] [ 7  8  9 10 11 12 13]
predictions: [92.7299375  85.2464297  58.63864305 58.63864305 58.157769
91 58.15776991
 58.15776991]
[ 0  1  2  3  4  5  6  7  8  9 10 11 12 13] [14 15 16 17 18 19 20]
predictions: [137.20978775 237.67045723 235.59156338 247.50361867 237.7
0859489
 129.49457213 237.51177326]
```

```
/Users/curtislisle/anaconda3/lib/python3.7/site-packages/ipykernel_laun
cher.py:16: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-d
ocs/stable/indexing.html#indexing-view-versus-copy
  app.launch_new_instance()
/Users/curtislisle/anaconda3/lib/python3.7/site-packages/ipykernel_laun
cher.py:16: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-d
ocs/stable/indexing.html#indexing-view-versus-copy
  app.launch_new_instance()
```

```
shape X: (21, 8)  y: (21,)
X_train: [[6000000229 15.0 43 12 2.5739754989400003 1.8378362654499998
   1.79587079551 0.438646405863]
  [6000000229 18.0 43 12 3.68080075639 2.36744244885 1.8551067013799998
   0.408555911681]
  [6000000229 32.0 43 12 3.52156761947 2.1588869598700002 1.89949729715
   0.41174904805699997]
  [6000000229 33.0 43 12 4.11011620995 2.32867843901 2.0060039562
   0.37723714851400003]
  [6000000229 35.0 43 12 4.54148736417 2.4329015929599995 2.07938224024
   0.356822503129]
  [6000000229 36.0 43 12 4.8873069110300005 2.58521277077 2.05632344159
   0.36767477536700005]
  [6000000229 38.0 43 12 5.14698001254 2.3288985602900003
   2.2908886088599996 0.333142630973]
  [6000000229 39.0 43 12 4.25946949764 2.26784149806 2.10182262649
   0.358463821769]
  [6000000229 40.0 43 12 3.8964829147300004 2.22098511942 2.00247878339
   0.384768582025]
  [6000000229 45.0 43 12 2.8163682310900002 1.8628993201
   1.8573201705000002 0.429078241983]
  [6000000229 117.0 43 12 2.24453098158 1.5814908358200002 1.86249881246
   0.42816006093099995]
  [6000000229 120.0 43 12 1.7908778722499998 1.42776860023
   1.7770380733000002 0.452859047107]
  [6000000229 65.0 43 12 1.25024641622 1.35570757444 1.4883810186200002
   0.515893468077]
  [6000000229 46.0 43 12 2.27981661519 1.6505514475100003 1.79946495083
   0.447543995985]] y_train: [ 17.  21.  74.  79.  91.  95. 111. 121. 12
8. 161. 377. 369. 274. 174.]
X_test: [[6000000229 55.0 43 12 3.7185708178 2.13013239662 1.9959821994
3
   0.39161586449]
  [6000000229 57.0 43 12 3.94892019427 2.23692584852 1.9816659251900002
   0.396669672488]
  [6000000229 60.0 43 12 4.05512052205 2.36636692021 1.9489290214400001
   0.395754811347]
  [6000000229 61.0 43 12 3.46176732466 2.09781207701 1.9133255732700003
   0.415151868705]
  [6000000229 62.0 43 12 4.04177708636 2.38057493253 1.92796543721
   0.40311240686800004]
  [6000000229 54.0 43 12 4.90461236614 2.53451985344 2.08562716497
   0.364313160423]
  [6000000229 64.0 43 12 3.99665060367 2.27025064956 1.9828958269699999
   0.39438861446999995]] y_test: [236. 242. 253. 261. 260. 225. 272.]
[0 1 2 3 4 5 6] [ 7  8  9 10 11 12 13]
predictions: [76.34865604 91.06491758 92.07945607 91.06491758 88.414035
5  63.14283945
 88.4140355 ]
[ 0  1  2  3  4  5  6  7  8  9 10 11 12 13] [14 15 16 17 18 19 20]
predictions: [217.77273998 168.1003571  168.1003571  240.99635919 227.1
3311416
 168.10023872 206.15192725]
finished generating 3 models
```

In [81]:

```
predictions2
```

Out[81]:

```
{(6000000228, 14, 40): 0.13974181153960463,
 (6000000229, 12, 43): 0.19126496002314552,
 (6000000464, 3, 51): -0.29243135338180615}
```

In [310]:

```
train.head()
```

Out[310]:

	column	range	date	season	day_offset	leaf_angle_alpha	leaf_angle_beta	leaf_ang
2017-05-13 12:00:00	2	43	2017-05-13 12:00:00	4	12	2.695956	1.977380	1.7
2017-05-13 12:00:00	15	35	2017-05-13 12:00:00	4	12	3.265980	2.018623	1.9
2017-05-13 12:00:00	2	42	2017-05-13 12:00:00	4	12	2.159610	1.809209	1.6
2017-05-13 12:00:00	4	30	2017-05-13 12:00:00	4	12	3.042180	2.198751	1.7
2017-05-15 12:00:00	2	45	2017-05-15 12:00:00	4	14	2.305345	1.872028	1.6

5 rows × 360 columns

In [311]:

```
train.tail()
```

Out[311]:

	column	range	date	season	day_offset	leaf_angle_alpha	leaf_angle_beta	leaf_ang
2017-07-04 12:00:00	3	48	2017-07-04 12:00:00	4	64	2.668148	1.771867	1.9
2017-07-04 12:00:00	4	48	2017-07-04 12:00:00	4	64	1.961894	1.573487	1.7
2017-07-04 12:00:00	7	49	2017-07-04 12:00:00	4	64	3.069223	2.013949	1.8
2017-07-04 12:00:00	12	49	2017-07-04 12:00:00	4	64	1.109560	1.352693	1.3
2017-07-04 12:00:00	15	54	2017-07-04 12:00:00	4	64	4.107072	2.462428	1.9

5 rows × 360 columns

In [ ]: