## Untitled

June 22, 2017

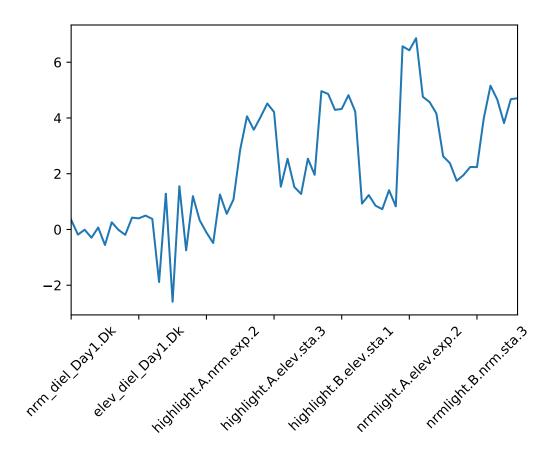
In [1]: import numpy as np

```
import pandas as pd
        import sklearn
        import matplotlib
        %matplotlib inline
        import matplotlib.pyplot as plt
        from IPython.display import set_matplotlib_formats
        set_matplotlib_formats('png', 'pdf')
In [2]: r1 = pd.read_csv('tps.ISB.ratios.tab', sep=' ')
        print(r1.shape)
        r1.head()
(12099, 67)
/Users/dreiss/miniconda3/lib/python3.6/site-packages/IPython/core/interactiveshell.py:2683: DtypeWarning: Columns
 interactivity=interactivity, compiler=compiler, result=result)
      nrm_diel_Day1.Dk nrm_diel_Day1.Lt nrm_diel_Day2.Dk nrm_diel_Day2.Lt \
1000
               -0.54922
                                  0.58181
                                                     0.10346
                                                                        0.42690
                                                    -1.00189
10002
               -1.24427
                                   1.19105
                                                                        0.86039
10006
               -0.36077
                                  -0.04452
                                                    -0.10789
                                                                       -0.09317
10008
               -1.96042
                                 -0.57802
                                                    -0.87794
                                                                       -2.17830
                0.02945
                                  -1.14524
                                                    -0.97718
                                                                        1.06226
10010
       nrm_diel_Day3.Dk nrm_diel_Day3.Lt nrm_diel_Day4.Dk nrm_diel_Day4.Lt
1000
                0.39565
                                                    -0.24153
                                   0.45545
                                                                       -0.84529
10002
               -1.04884
                                   0.83065
                                                    -0.83815
                                                                        0.29552
10006
                0.46013
                                  -0.13913
                                                     0.37880
                                                                       -0.27903
10008
                0.93808
                                                     1.55504
                                                                        0.56126
                                  1.19216
10010
               -0.16960
                                  -0.50967
                                                     0.59087
                                                                       -0.91881
       nrm_diel_Day5.Dk nrm_diel_Day5.Lt
1000
               -0.39492
                                   0.42528
10002
                0.30941
                                   1.45448
                                                    . . .
10006
                0.58274
                                   0.20985
10008
                2.55721
                                   2.44418
                                                    . . .
10010
               -0.33980
                                   3.03597
       nrmlight.B.nrm.exp.3 nrmlight.B.nrm.sta.1 nrmlight.B.nrm.sta.2 \
1000
                   -0.02569
                                          -0.60172
                                                                 -0.21575
10002
                    0.27507
                                          -0.48276
                                                                 -0.05589
10006
                    0.45859
                                           0.51178
                                                                  0.88394
                   -0.68742
10008
                                           0.04835
                                                                  1.35192
10010
                   -0.73207
                                          -0.31512
                                                                 -0.08387
```

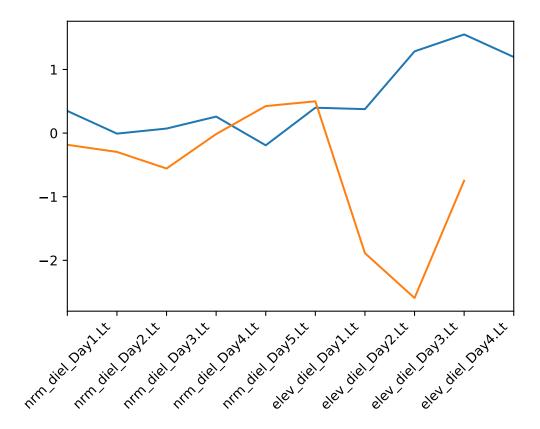
```
nrmlight.B.nrm.sta.3 nrmlight.B.elev.exp.1 nrmlight.B.elev.exp.2 \
1000
                                        -0.29853
                  -0.32312
                                                                -0.24846
10002
                  -0.37492
                                          0.44073
                                                                 0.60202
10006
                   0.54188
                                          0.66271
                                                                  1.68050
10008
                   0.53908
                                          -0.12631
                                                                 -0.86967
                                          -0.52712
10010
                  -0.14934
                                                                 -0.73413
      nrmlight.B.elev.exp.3 nrmlight.B.elev.sta.1 nrmlight.B.elev.sta.2 \
1000
                    0.20443
                                          -0.96469
                                                                  -0.73780
10002
                     0.42461
                                           -0.77719
                                                                  -0.16530
10006
                    0.48628
                                           0.86174
                                                                   0.62019
10008
                    1.06930
                                           0.28077
                                                                   0.18448
10010
                    -0.06333
                                           -0.24718
                                                                  -0.07036
      nrmlight.B.elev.sta.3
1000
                   -0.29041
10002
                    0.20979
10006
                    1.07254
10008
                    0.91407
10010
                    -0.39420
[5 rows x 67 columns]
In [3]: import re
       def grepl(pattern, strings, values=False):
            out = np.array([bool(re.search(pattern, i)) for i in strings])
            if values:
               out = strings[out]
           return out
        #def grepl(pattern, strings):
            pd.Series(strings).str.contains(pattern).tolist()
In [4]: colnames = r1.columns.values
       print(colnames)
       print(grepl('Dk', colnames))
       colnames[grepl('Dk', colnames)]
['nrm_diel_Day1.Dk' 'nrm_diel_Day1.Lt' 'nrm_diel_Day2.Dk'
 'nrm_diel_Day2.Lt' 'nrm_diel_Day3.Dk' 'nrm_diel_Day3.Lt'
 'nrm_diel_Day4.Dk' 'nrm_diel_Day4.Lt' 'nrm_diel_Day5.Dk'
 'nrm_diel_Day5.Lt' 'elev_diel_Day1.Dk' 'elev_diel_Day1.Lt'
 'elev_diel_Day2.Dk' 'elev_diel_Day2.Lt' 'elev_diel_Day3.Dk'
 'elev_diel_Day3.Lt' 'elev_diel_Day4.Dk' 'elev_diel_Day4.Lt'
 'elev_diel_Day5.Dk' 'highlight.A.nrm.exp.1' 'highlight.A.nrm.exp.2'
 'highlight.A.nrm.exp.3' 'highlight.A.nrm.sta.1' 'highlight.A.nrm.sta.2'
 'highlight.A.nrm.sta.3' 'highlight.A.elev.exp.1' 'highlight.A.elev.exp.2'
 'highlight.A.elev.exp.3' 'highlight.A.elev.sta.1' 'highlight.A.elev.sta.2'
 'highlight.A.elev.sta.3' 'highlight.B.nrm.exp.1' 'highlight.B.nrm.exp.2'
 'highlight.B.nrm.exp.3' 'highlight.B.nrm.sta.1' 'highlight.B.nrm.sta.2'
 'highlight.B.nrm.sta.3' 'highlight.B.elev.exp.1' 'highlight.B.elev.exp.2'
 'highlight.B.elev.exp.3' 'highlight.B.elev.sta.1' 'highlight.B.elev.sta.2'
 'highlight.B.elev.sta.3' 'nrmlight.A.nrm.exp.1' 'nrmlight.A.nrm.exp.2'
 'nrmlight.A.nrm.exp.3' 'nrmlight.A.nrm.sta.1' 'nrmlight.A.nrm.sta.2'
 'nrmlight.A.nrm.sta.3' 'nrmlight.A.elev.exp.1' 'nrmlight.A.elev.exp.2'
 'nrmlight.A.elev.exp.3' 'nrmlight.A.elev.sta.1' 'nrmlight.A.elev.sta.2'
 'nrmlight.A.elev.sta.3' 'nrmlight.B.nrm.exp.1' 'nrmlight.B.nrm.exp.2'
 'nrmlight.B.nrm.exp.3' 'nrmlight.B.nrm.sta.1' 'nrmlight.B.nrm.sta.2'
 'nrmlight.B.nrm.sta.3' 'nrmlight.B.elev.exp.1' 'nrmlight.B.elev.exp.2'
```

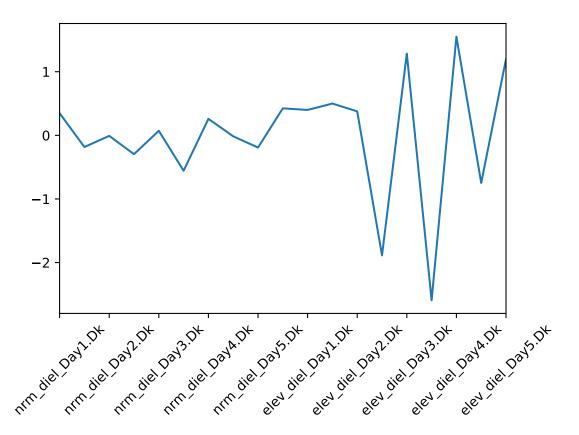
```
'nrmlight.B.elev.exp.3' 'nrmlight.B.elev.sta.1' 'nrmlight.B.elev.sta.2'
  'nrmlight.B.elev.sta.3']
 [ True False True False True False True False True False True False
    True False True False True False False False False False
 False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False 
  False False False False False False False False False False False
  False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False False 
  False False False False False False]
Out[4]: array(['nrm_diel_Day1.Dk', 'nrm_diel_Day2.Dk', 'nrm_diel_Day3.Dk',
                                'nrm_diel_Day4.Dk', 'nrm_diel_Day5.Dk', 'elev_diel_Day1.Dk'
                                'elev_diel_Day2.Dk', 'elev_diel_Day3.Dk', 'elev_diel_Day4.Dk',
                                'elev_diel_Day5.Dk'], dtype=object)
      From Justin (it's in R):
condclasses = list(
a dark12hr = function(x){ grepl('Dk',x) },
a light12hr = function(x){ grepl('Lt',x) },
a exponential_diel = function(x){ grepl('diel_Day[12]',x) | grepl('diel_Day3.Dk',x) },
a stationary_diel = function(x){ grepl('diel_Day[45]',x) | grepl('diel_Day3.Lt',x) },
a exponential_24light = function(x){ grepl('nrmlight.+exp',x) },
a stationary_24light = function(x){ grepl('nrmlight.+sta',x) },
ă exponential_24highlight = function(x){ grepl('highlight.+exp',x) },
a stationary_24highlight = function(x){ grepl('highlight.+sta',x) },
a highlight_arrays = function(x){ grepl('highlight',x) },
a normallight_arrays = function(x){ grepl('nrmlight',x) },
a co2_elevated_arrays = function(x){ grepl('elev',x) & !grepl('diel',x) },
a co2_elevated_expo_arrays = function(x){ grepl('elev',x) & grepl('\\.exp',x) & !grepl('diel',x) },
ă co2_elevated_stat_arrays = function(x){ grepl('elev',x) & grepl('\\.sta',x) & !grepl('diel',x) },
a co2_moderate_arrays = function(x){ grepl('nrm',x) & !grepl('elev',x) & !grepl('diel',x) },
ă co2_moderate_expo_arrays = function(x){ grepl('nrm',x) & grepl('\\.exp',x) & !grepl('elev',x) & !grepl('diel',x)
ă co2_moderate_stat_arrays = function(x){ grepl('nrm',x) & grepl('\\.sta',x) & !grepl('elev',x) & !grepl('diel',x)
In [5]: # Convert to python:
                 condclasses = {
                     'dark12hr': lambda x: grepl('Dk',x),
                      'light12hr': lambda x: grepl('Lt',x),
                      'exponential_diel': lambda x: grepl('diel_Day[12]',x) | grepl('diel_Day3.Dk',x),
                      'stationary_diel': lambda x: grepl('diel_Day[45]',x) | grepl('diel_Day3.Lt',x),
                      'exponential_24light': lambda x: grepl('nrmlight.+exp',x),
                      'stationary_24light': lambda x: grepl('nrmlight.+sta',x),
                      'exponential_24highlight': lambda x: grepl('highlight.+exp',x),
                      'stationary_24highlight': lambda x: grepl('highlight.+sta',x),
                      'highlight_arrays': lambda x: grepl('highlight',x),
                      'normallight_arrays': lambda x: grepl('nrmlight',x),
                      'co2_elevated_arrays': lambda x: grepl('elev',x), # & ~grepl('diel',x),
                      'co2_elevated_expo_arrays': lambda x: grepl('elev',x) & grepl('\.exp',x), # & ~grepl('diel',x),
                      'co2_elevated_stat_arrays': lambda x: grepl('elev',x) & grepl('\.sta',x), # & ~grepl('diel',x),
                      'co2_moderate_arrays': lambda x: grepl('nrm',x) & ~grepl('elev',x), # & ~grepl('diel',x),
                      'co2_moderate_expo_arrays': lambda x: grepl('nrm',x) & grepl('\.exp',x), # & ~grepl('elev',x) & ~grepl('
                      'co2_moderate_stat_arrays': lambda x: grepl('nrm',x) & grepl('\.sta',x), # & ~grepl('elev',x) & ~grepl('
In [6]: colnames[condclasses['dark12hr'](colnames)]
Out[6]: array(['nrm_diel_Day1.Dk', 'nrm_diel_Day2.Dk', 'nrm_diel_Day3.Dk',
                                'nrm_diel_Day4.Dk', 'nrm_diel_Day5.Dk', 'elev_diel_Day1.Dk'
                                'elev_diel_Day2.Dk', 'elev_diel_Day3.Dk', 'elev_diel_Day4.Dk',
                                'elev_diel_Day5.Dk'], dtype=object)
```

```
In [7]: the_gene = 262258
          ax = r1.loc[the_gene].plot()
          ax.set_xticklabels(ax.xaxis.get_majorticklabels(), rotation=45);
```



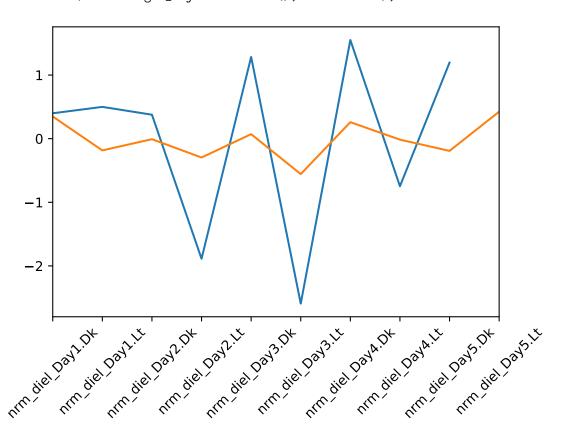
```
In [8]: isdark = condclasses['dark12hr'](colnames)
    islight = condclasses['light12hr'](colnames)
    ax = r1.loc[the_gene, colnames[isdark]].plot()
    ax = r1.loc[the_gene, colnames[islight]].plot()
    ax.set_xticklabels(ax.xaxis.get_majorticklabels(), rotation=45);
```



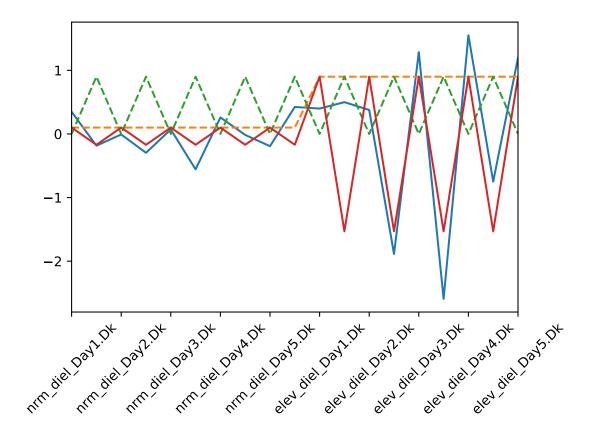


```
#print(colnames[light])
         isco2_high = condclasses['co2_elevated_arrays'](colnames)
         isco2_low = condclasses['co2_moderate_arrays'](colnames)
         #print(colnames[co2_high])
In [11]: print(colnames[(isdark | islight) & isco2_high])
         print(colnames[(isdark | islight) & isco2_low])
['elev_diel_Day1.Dk' 'elev_diel_Day1.Lt' 'elev_diel_Day2.Dk'
 'elev_diel_Day2.Lt' 'elev_diel_Day3.Dk' 'elev_diel_Day3.Lt'
 'elev_diel_Day4.Dk' 'elev_diel_Day4.Lt' 'elev_diel_Day5.Dk']
['nrm_diel_Day1.Dk' 'nrm_diel_Day1.Lt' 'nrm_diel_Day2.Dk'
 'nrm_diel_Day2.Lt' 'nrm_diel_Day3.Dk' 'nrm_diel_Day3.Lt'
 'nrm_diel_Day4.Dk' 'nrm_diel_Day4.Lt' 'nrm_diel_Day5.Dk'
 'nrm_diel_Day5.Lt']
In [12]: ax = r1.loc[the_gene, colnames[(isdark | islight) & isco2_high]].plot()
         ax = r1.loc[the_gene, colnames[(isdark | islight) & isco2_low]].plot()
         ax.set_xticklabels(ax.xaxis.get_majorticklabels(), rotation=45);
```

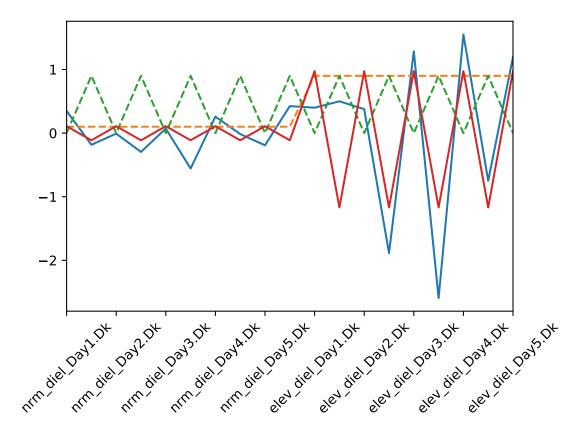
In [10]: #print(colnames[dark])

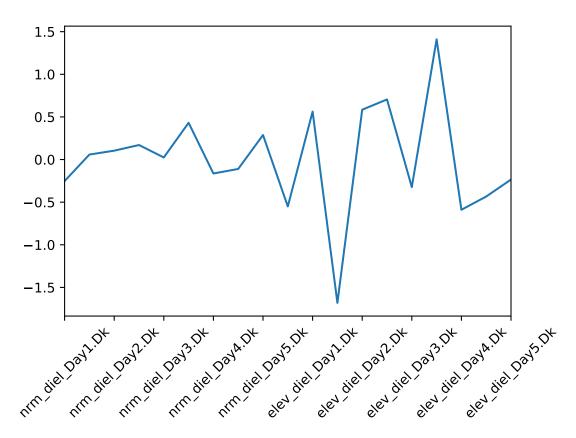


Note here I call it 'isdark' but it's actually tracing the light since it is set to 0.1 for dark and 0.9 for light:



```
In [14]: from sklearn import linear_model
         y = r1.loc[the_gene, colnames[(isdark | islight)]]
         x = np.vstack((np.ones_like(y),
                        co2[isdark | islight],
                        dark[isdark | islight],
                        (co2*dark)[isdark | islight]))
         print(x.shape, y.shape)
         reg = linear_model.LinearRegression()
         reg.fit(x.T, y) #, sample_weight=np.abs(y))
         print(reg.score(x.T, y)) # R^2
         reg.coef_
(4, 19) (19,)
0.583197557061
Out[14]: array([ 0.
                           , 1.08214
                                        , 0.02106882, -2.66937708])
In [15]: ax = r1.loc[the_gene, colnames[(isdark | islight)]].plot()
         ax.set_xticklabels(ax.xaxis.get_majorticklabels(), rotation=45);
         ax.plot(co2[isdark | islight], ls='dashed')
         ax.plot(dark[isdark | islight], ls='dashed')
         ax.plot(reg.coef_[3] * (co2*dark)[isdark | islight] +
                 reg.coef_[1] * co2[isdark | islight] +
                 reg.coef_[2] * dark[isdark | islight])
Out[15]: [<matplotlib.lines.Line2D at 0x11cb194e0>]
```





Lets use statsmodels to get errors on coefficients.

```
In [17]: import statsmodels.api as sm
    results = sm.OLS(y, x.T).fit()
    results.summary()
```

/Users/dreiss/miniconda3/lib/python3.6/site-packages/statsmodels/compat/pandas.py:56: FutureWarning: The pandas.com from pandas.core import datetools

/Users/dreiss/miniconda3/lib/python3.6/site-packages/scipy/stats/stats.py:1334: UserWarning: kurtosistest only val: "anyway, n=%i" % int(n))

Out[17]: <class 'statsmodels.iolib.summary.Summary'>

## OLS Regression Results

=======================================			
Dep. Variable:	262258	R-squared:	0.583
Model:	OLS	Adj. R-squared:	0.500
Method:	Least Squares	F-statistic:	6.996
Date:	Thu, 22 Jun 2017	Prob (F-statistic):	0.00363
Time:	15:07:46	Log-Likelihood:	-17.982
No. Observations:	19	AIC:	43.96
Df Residuals:	15	BIC:	47.74
Df Model:	3		

Covariance Type: nonrobust

========			=======	========		========
	coef	std err	t	P> t	[0.025	0.975]
const	-0.0125	0.355	-0.035	0.972	-0.770	0.745
x1	1.0821	0.555	1.951	0.070	-0.100	2.264
x2	0.0211	0.559	0.038	0.970	-1.169	1.212
x3	-2.6694	0.898	-2.971	0.010	-4.584	-0.754
========	========	=======	=======	========		========
Omnibus:		4	.009 Durb	in-Watson:		2.851
Prob(Omnib	ous):	0	.135 Jarq	ue-Bera (JB)	):	2.024
Skew:		0	.354 Prob	(JB):		0.363
Kurtosis:		4	.433 Cond	. No.		8.56

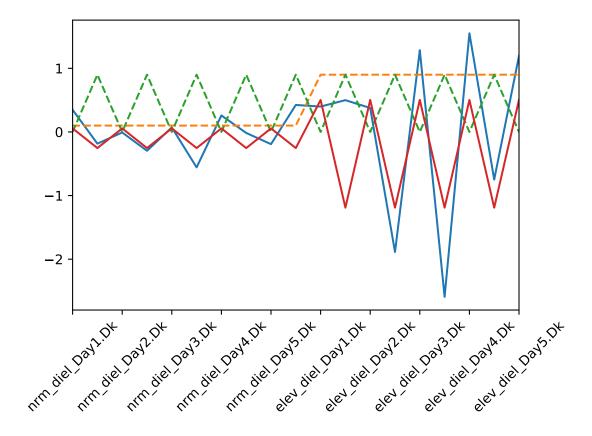
#### Warnings:

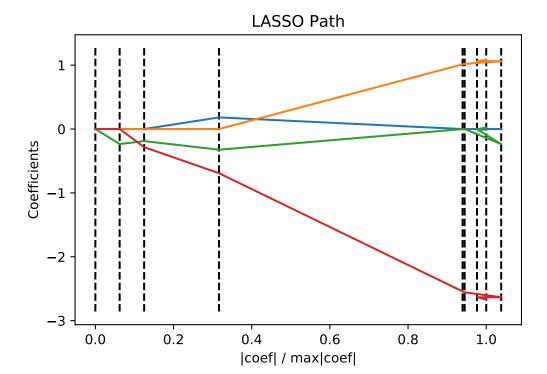
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

## Try Lasso...

## 0.548514155569

[ 0. 0.55873282 -0.15137112 -1.92173963]





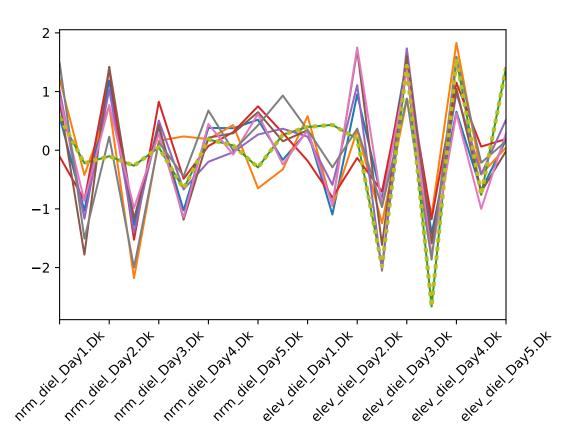
Try k-means to get a cluster containing this super awesome gene...

In [20]: from sklearn.preprocessing import scale

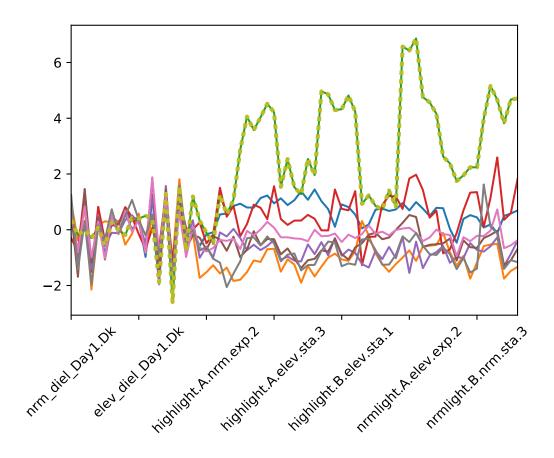
```
print(r1.shape)
         print(np.mean(np.isnan(r1.values)))
         r1norm = r1.dropna(axis=0, how='all', thresh=None, subset=None, inplace=False)
         print(r1norm.shape)
         r1norm = r1norm.loc[:, colnames[(isdark | islight)]]
         #print(np.mean(np.isnan(r1norm)))
         r1norm.fillna(0., inplace=True)
         r1norm.values[:, :] = scale(r1norm.values)
         print(r1norm.shape)
(12099, 67)
0.0190554788665
(12099, 67)
(12099, 19)
In [21]: from sklearn.cluster import KMeans
         np.random.seed(4)
         km = KMeans(n_clusters=1200, init='k-means++', n_init=10, max_iter=20,
                     tol=0.0001, precompute_distances='auto', verbose=0, random_state=None,
                     copy_x=True, n_jobs=1, algorithm='auto')
         km.fit(r1norm)
         labels = km.labels_
         print(len(labels))
         labels
12099
Out[21]: array([713, 618, 878, ..., 226, 226, 654], dtype=int32)
In [22]: index = labels[np.where(r1.index.values == the_gene)]
         print(index)
```

```
genes = r1.index.values[np.where(labels == index)]
         print(len(genes))
         print(the_gene in genes)
         print(genes)
         ax = r1norm.loc[genes].T.plot(legend=False)
         plt.plot(r1norm.loc[the_gene, :].values, ls='dotted', lw=3)
         ax.set_xticklabels(ax.xaxis.get_majorticklabels(), rotation=45);
[601]
True
[14096 25744 262258 264821 34170 '6010' '9135' '9976']
```

8

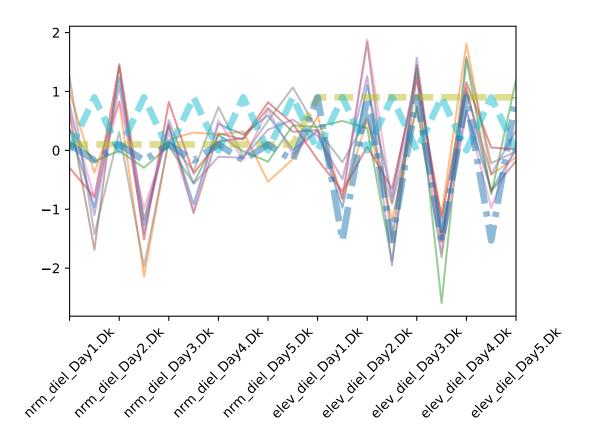


```
In [23]: ax = r1.loc[genes].T.plot(legend=False)
         plt.plot(r1.loc[the_gene, :].values, ls='dotted', lw=3)
         ax.set_xticklabels(ax.xaxis.get_majorticklabels(), rotation=45);
```



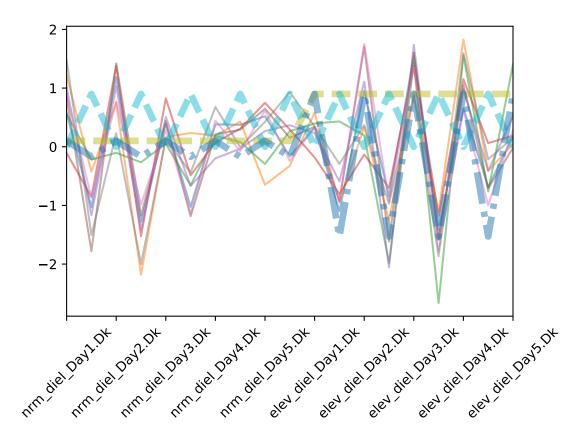
```
In [24]: ax = r1.loc[genes, colnames[(isdark | islight)]].T.plot(legend=False, alpha=0.5)
         ax.set_xticklabels(ax.xaxis.get_majorticklabels(), rotation=45)
         ax.plot(co2[isdark | islight], ls='dashed', lw=5, alpha=0.5)
         ax.plot(dark[isdark | islight], ls='dashed', lw=5, alpha=0.5)
         ax.plot(-3. * (co2*dark)[isdark | islight] + 1. * co2[isdark | islight], lw=5, alpha=0.5, ls='dashdot')
```

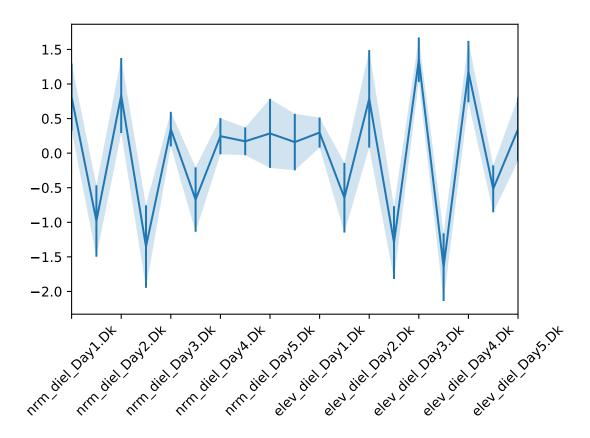
Out[24]: [<matplotlib.lines.Line2D at 0x11c5bf978>]



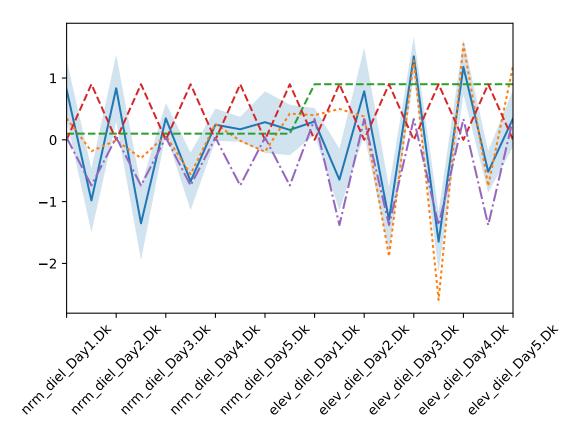
```
In [25]: r1a = r1.copy()
        r1a.loc[:, colnames[(isdark | islight)]] = r1norm
         ax = r1a.loc[genes, colnames[(isdark | islight)]].T.plot(legend=False, alpha=0.5)
         ax.set_xticklabels(ax.xaxis.get_majorticklabels(), rotation=45)
         ax.plot(co2[isdark | islight], ls='dashed', lw=5, alpha=0.5)
         ax.plot(dark[isdark | islight], ls='dashed', lw=5, alpha=0.5)
         ax.plot(-3. * (co2*dark)[isdark | islight] + 1. * co2[isdark | islight], lw=5, alpha=0.5, ls='dashdot')
```

Out[25]: [<matplotlib.lines.Line2D at 0x11cccd2b0>]





```
In [27]: reg = linear_model.LinearRegression()
         reg.fit(x.T, mn, sample_weight=1/err)
         print(reg.score(x.T, y, sample_weight=1/err)) # R^2
         reg.coef_
0.514930892128
Out[27]: array([ 0.
                              0.37437859, -0.73216368, -1.30594988])
In [28]: ax = mn.plot() #yerr=err)
         ax.set_xticklabels(ax.xaxis.get_majorticklabels(), rotation=45);
         ax.fill_between(range(len(mn)), mn-err, mn+err, alpha=0.2)
         ax.plot(r1.loc[the_gene, colnames[(isdark | islight)]].values, ls='dotted')
         ax.plot(co2[isdark | islight], ls='dashed')
         ax.plot(dark[isdark | islight], ls='dashed')
         ax.plot(reg.coef_[3] * (co2*dark)[isdark | islight] +
                 reg.coef_[1] * co2[isdark | islight] +
                 reg.coef_[2] * dark[isdark | islight], ls='dashdot')
Out[28]: [<matplotlib.lines.Line2D at 0x11d9387f0>]
```



/Users/dreiss/miniconda3/lib/python3.6/site-packages/scipy/stats/stats.py:1334: UserWarning: kurtosistest only val: "anyway, n=%i" % int(n))

Out[29]: <class 'statsmodels.iolib.summary.Summary'>

## WLS Regression Results

Dep. Variable Model: Method: Date: Time: No. Observat Df Residuals Df Model: Covariance T	ions:	-	WLS ares 2017 9:00 19 15 3	Adj. F-sta Prob	ared: R-squared: tistic: (F-statistic): ikelihood:		0.603 0.523 7.588 0.00257 -13.191 34.38 38.16
	coef	std err		t	P> t	[0.025	0.975]
const x1 x2 x3	0.3465 -0.4321	0.360 0.366	0. -1.	962 182	0.143 0.351 0.256 0.036	-0.421 -1.211	1.114 0.347
Omnibus: Prob(Omnibus Skew:	3):	0	.436		n-Watson: le-Bera (JB): (JB):		2.906 0.931 0.628

Kurtosis: 1.915 Cond. No. 8.22

\_\_\_\_\_\_

#### Warnings:

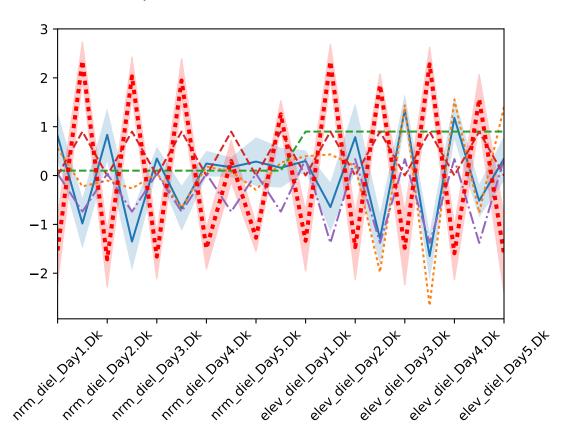
1198 0.8879071125

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified. """

Find clusters that may be anticorrelated with the\_gene.

```
In [30]: def get_cluster_profile(ind):
             genes = r1.index.values[np.where(labels == ind)]
             mn1 = r1a.loc[genes, colnames[(isdark | islight)]].mean()
             err1 = r1a.loc[genes, colnames[(isdark | islight)]].std()
             return mn1, err1
         for lab in range(max(labels)):
             mn1, _ = get_cluster_profile(lab)
             corr = np.corrcoef(mn1, mn)[0, 1]
             if np.abs(corr) > 0.85:
                 print(lab, corr)
16 0.875917093914
17 -0.886837101736
26 0.913622075356
51 0.947320514238
58 0.900811857266
103 -0.878456522929
112 0.934666079963
170 -0.893175978822
174 0.879700896006
180 0.932091999425
235 0.902334600112
264 0.881464889712
309 0.913380606222
381 0.870723547997
384 0.85208112038
439 0.931438462027
443 0.934761774506
464 0.854619922791
495 -0.852214388152
528 -0.885249195782
535 0.918347994424
552 0.869160951163
601 1.0
646 0.876867077841
650 0.883170107871
719 0.904411250974
731 0.880618583152
749 0.92443441189
751 0.878472346778
803 0.900515585077
917 -0.868159627678
935 0.928134219879
956 0.851196891911
1042 -0.860309777686
1067 0.923141483006
1126 0.910982499787
1146 0.860771335809
1149 -0.884697663519
```

Out[31]: <matplotlib.collections.PolyCollection at 0x110b46390>



/Users/dreiss/miniconda3/lib/python3.6/site-packages/scipy/stats/stats.py:1334: UserWarning: kurtosistest only val: "anyway, n=%i" % int(n))

```
Out[32]: <class 'statsmodels.iolib.summary.Summary'>
```

#### WLS Regression Results

===========			=========
Dep. Variable:	у	R-squared:	0.933
Model:	WLS	Adj. R-squared:	0.920
Method:	Least Squares	F-statistic:	70.00
Date:	Thu, 22 Jun 2017	<pre>Prob (F-statistic):</pre>	4.75e-09

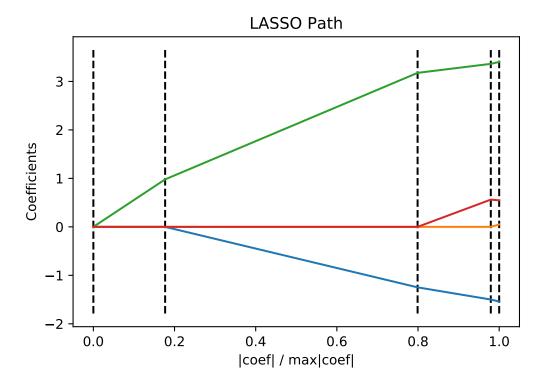
Time:	15:09:05	Log-Likelihood:	-12.514
No. Observations:	19	AIC:	33.03
Df Residuals:	15	BIC:	36.80
Df Model:	3		

Covariance Type: nonrobust

=======	========	========	========		========	
	coef	std err	t	P> t	[0.025	0.975]
const	-1.4441	0.247	-5.851	0.000	-1.970	-0.918
x1	-0.0572	0.504	-0.114	0.911	-1.131	1.017
x2	3.2510	0.364	8.931	0.000	2.475	4.027
х3	0.7214	0.671	1.076	0.299	-0.708	2.151
=======	=======	=======				
Omnibus:		5.	871 Durbir	n-Watson:		2.496
Prob(Omnib	us):	0.	053 Jarque	e-Bera (JB):		3.527
Skew:		-0.	660 Prob(J	IB):		0.171
Kurtosis:		4.	646 Cond.	No.		10.7

## Warnings:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.



#### In []:

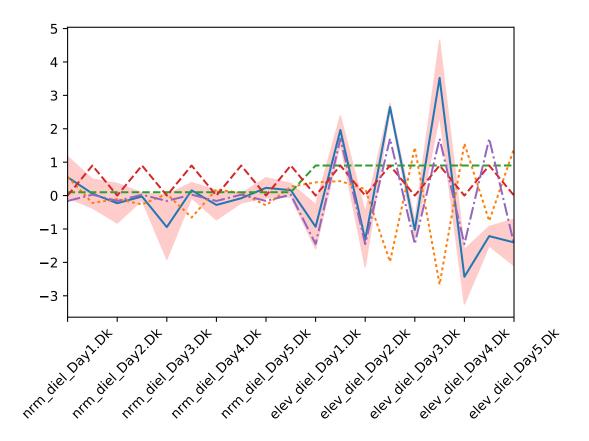
Try fitting all clusters, see if we can find different combo's of coefficients. Especially look for ones which only are affected by co2 (param x1, or index 1).

```
In [34]: reg = linear_model.LinearRegression()
         def fit_cluster(ind):
             mn, std = get_cluster_profile(ind)
             reg.fit(x.T, mn) #, sample_weight=np.abs(y))
             score = reg.score(x.T, mn) # R^2
             return reg.coef_, score
         scores = [fit_cluster(ind) for ind in range(1200)]
In [35]: \#co2\_coeffs = np.array([sc[0][1] for sc in scores])
         #print(np.min(co2_coeffs), np.max(co2_coeffs))
         #lab = np.argmin(co2_coeffs)
         #print(lab)
         #print(scores[lab])
         for i in range(1200):
             sc = scores[i]
             if np.abs(sc[0][1]) > np.abs(sc[0][2]) + np.abs(sc[0][3]): # and sc[1] > 0.4:
                 print(i, sc)
         # Not finding much!
7 (array([ 0.
                        0.02805658, -0.01060968, -0.01539051), 0.014527977498730138)
123 (array([ 0.
                          0.13014645, 0.01530956, -0.06231341]), 0.0053610042689555826)
                        -0.18053608, -0.12957559, 0.02376715]), 0.0024103419863978903)
153 (array([ 0.
                         0.1339631 , 0.01378686, -0.05484272]), 0.0027783321125754985)
209 (array([ 0.
273 (array([ 0.
                          0.16378924, 0.10021357, -0.04324233]), 0.015875872136872027)
                          0.10394438, 0.0102262, -0.0160302]), 0.0064332734534413571)
329 (array([ 0.
```

```
351 (array([ 0.
                     , 0.49059658, -0.04136066, -0.18041325]), 0.0033111682453613733)
                      , -0.28258216, 0.04348452, 0.10745876]), 0.0054957613118427062)
422 (array([ 0.
                     , -0.14819229, -0.07165215, 0.01274871]), 0.011380127029799403)
480 (array([ 0.
                     , 0.26590792, 0.01590301, -0.13498175]), 0.0087819132474280526)
564 (array([ 0.
                     , -0.88246099, -0.4512164 , 0.16506981]), 0.015400235591607081)
570 (array([ 0.
                     , 0.10831328, 0.04421293, 0.00537372]), 0.0084467502221186042)
822 (array([ 0.
1069 (array([ 0.
                       , -0.40087296, 0.08233548, 0.26586085]), 0.010932752350386599)
  Try to look for all cases of high interaction (co2 * light):
In [36]: print(scores[601])
        for i in range(1200):
            sc = scores[i]
            if np.abs(sc[0][3]) > 1. and np.abs(sc[0][3]) > 2.*np.abs(sc[0][2]) and sc[1] > 0.4:
                print(i, sc)
                  , 0.35925953, -1.04670126, -1.08165068]), 0.71631563247766072)
(array([ 0.
                    , -1.15503253, 0.47029975, 2.98318686]), 0.51592706479888784)
459 (array([ 0.
755 (array([ 0.
                      , -1.6113901 , -0.20309454, 4.11958912]), 0.58824159983905022)
                      , -0.63498353, 0.49535103, 1.50899811]), 0.55388881195919604)
1105 (array([ 0.
In [37]: mn1, err1 = get_cluster_profile(755)
        ax = mn1.plot()
        #ax.plot(mn1.values, ls='dotted', lw=3, c='r')
        ax.set_xticklabels(ax.xaxis.get_majorticklabels(), rotation=45);
        ax.fill_between(range(len(mn1)), mn1-err1, mn1+err1, alpha=0.2, color='r')
        ax.plot(r1a.loc[the_gene, colnames[(isdark | islight)]].values, ls='dotted')
        ax.plot(co2[isdark | islight], ls='dashed')
        ax.plot(dark[isdark | islight], ls='dashed')
```

coef[2] \* dark[isdark | islight], ls='dashdot')

coef = scores[755][0]



# In []: