In [1]:
```
import numpy as np
import pandas as pd
import seaborn.apionly as sns
import matplotlib.pyplot as plt
from tqdm import tqdm_notebook
%matplotlib inline

import os
import codecs
import sys
import textacy
```

Automated Tagging of Maintenance Issues:

A Keyword Detection and Ranking Approach

Thurston Sexton + Mike Brundage

Also: compared to a Machine Learning one

In [2]:
```
data_directory = os.path.join('.', 'data')
raw_excel_filepath = os.path.join(data_directory, 'tag_data2.xlsx')
raw_csv_filepath = os.path.join(data_directory, 'raw_csv_tagged.csv')
vocab_filepath = os.path.join(data_directory, 'tag_vocab.csv')
```

In [3]:
```
# read in the tagged issues, which have been cleaned of nasty unicode and combined Description+Resolut
ion
df_raw = pd.read_csv(raw_csv_filepath, encoding=sys.getfilesystemencoding(),
                     names = ['RawText','p_Item','p_Action','s_Action','s_Item'])
# df_raw.head()

# read in the keyword dictionary and to some data-munging.
df_vocab = pd.read_csv(vocab_filepath, header=0, encoding=sys.getfilesystemencoding(),
                       names = ['token', 'NE','alias','note'], index_col=0)
df_vocab = df_vocab.dropna(subset=['NE'])  # remove named entities that are NaN
df_vocab.alias = df_vocab.apply(lambda x: np.where(pd.isnull(x.alias), x.name, x.alias), axis=1) # ali
as to original if blank
df_vocab = df_vocab[~df_vocab.index.duplicated(keep='first')]
```

In [62]:
```
df_vocab.head(10)
```

Out[62]:

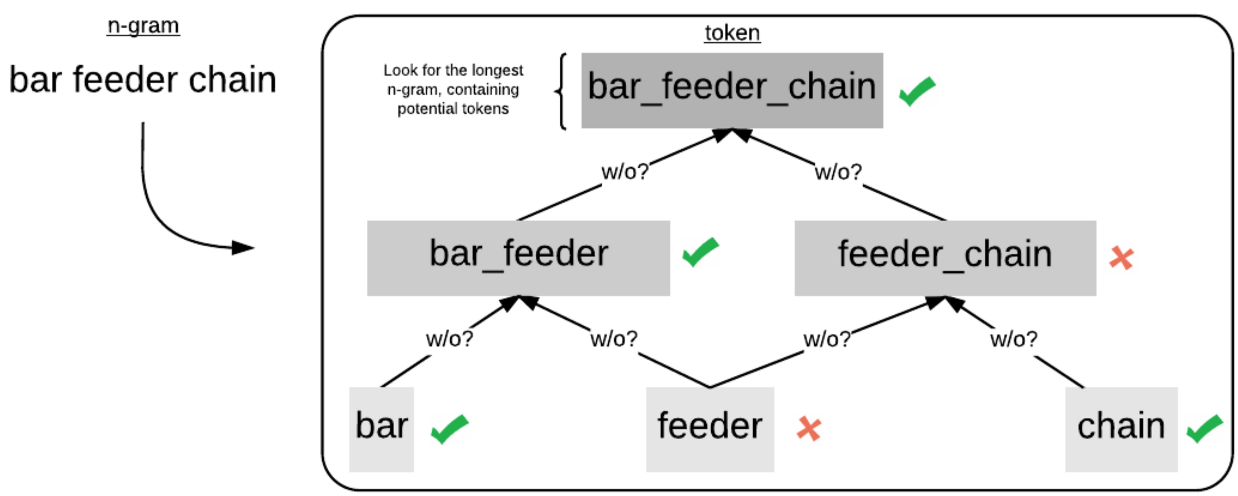
	NE	alias	note
token			
replace	S	replace	NaN
unit	I	unit	NaN
motor	I	motor	NaN
spindle	I	spindle	NaN
leak	P	leak	NaN
valve	I	valve	NaN
replaced	S	replace	NaN
fault	P	fault	NaN
bar	I	bar	NaN
inop	P	inoperable	NaN

In [5]:
```
# how many instances of each keyword class are there?
print 'named entities: '
print 'I\tItem\nP\tProblem\nS\tSolution\nR\tRedundant'
print 'U\tUnknown\nX\tStop Word'
df_vocab.groupby("NE").nunique()
```

```
named entities:
I	Item
P	Problem
S	Solution
R	Redundant
U	Unknown
X	Stop Word
```

Out[5]:

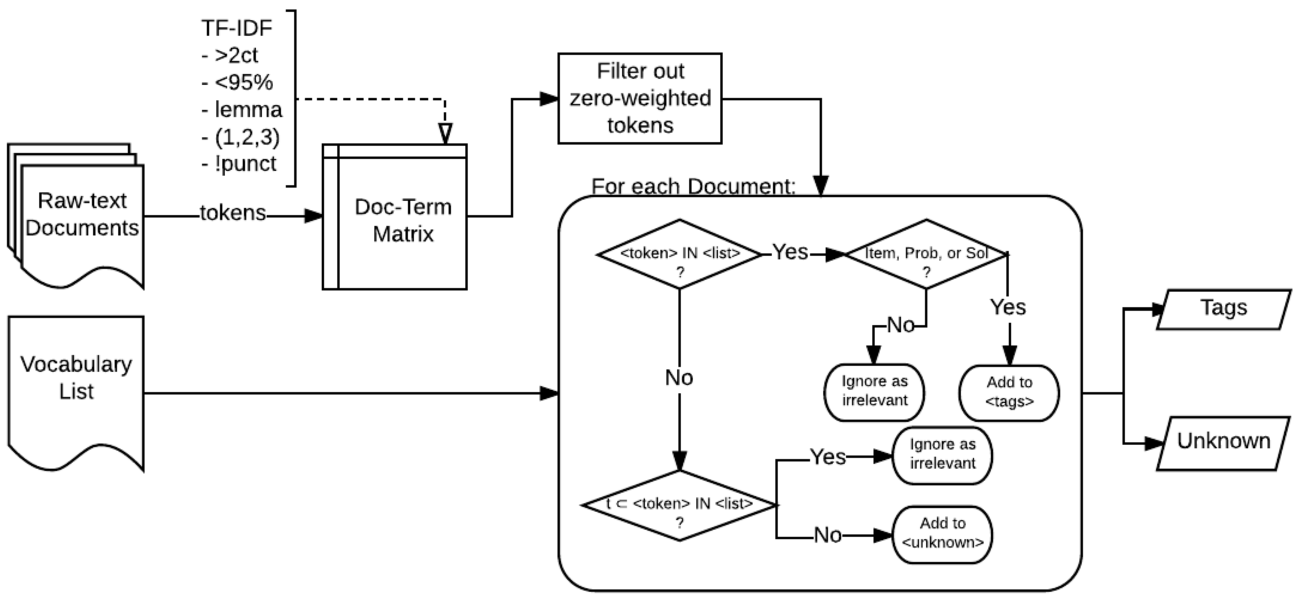
	NE	alias	note
NE			
I	1	500	25
P	1	114	16
R	1	148	0
S	1	82	14
U	1	100	9
X	1	184	5




```
# start up our NLP engine, Spacy wrapped in Textacy
docs = textacy.fileio.read.read_csv(raw_csv_filepath, encoding='utf-8')

content_stream, metadata_stream = textacy.fileio.split_record_fields(docs, 1)  # Descriptions in Col 6
corpus = textacy.Corpus(u'en', texts=content_stream, metadatas=metadata_stream)
```

In [6]:
```
# start up our NLP engine, Spacy wrapped in Textacy
docs = textacy.fileio.read.read_csv(raw_csv_filepath, encoding='utf-8')

content_stream, metadata_stream = textacy.fileio.split_record_fields(docs, 1)  # Descriptions in Col 6
corpus = textacy.Corpus(u'en', texts=content_stream, metadatas=metadata_stream)
```

```
# THIS GENERATED THE TOP N MOST IMPORTANT TOKENS VIA A DOC_TERM_MATRIX
# the engineers used this code-snippet to make tag_vocab.csv

from unicodedata import normalize

topn = 3000
topn_tok = [id2term[i] for i in doc_term_matrix.sum(axis=0).argsort()[0,-topn:].tolist()[0][::-1]]
with open('new_top{}.txt'.format(topn), 'wb') as f:
    for i in topn_tok:
        try:
            f.write(i+'\n')
        except UnicodeEncodeError:
            print i, '-->', normalize('NFKD', i).encode('ascii','ignore')
            f.write(normalize('NFKD', i).encode('ascii','ignore') +'\n')
```



In [7]:
```python
def get_norm_tokens(doc_n, doc_term_mat, id2term):
    doc = doc_term_mat[doc_n].toarray()
    return [id2term[i] for i in doc.nonzero()[1]]

def doc_to_tags(tokens, thes):
#     tokens = get_norm_terms(doc)
    tags = {'I':[], 'P':[], 'S':[]}
    untagged = []
    vocab_list = thes.index.tolist()
    for tok in tokens:
        if tok in vocab_list:  # recognized token?
            typ = thes.loc[tok]['NE']

            if typ in tags.keys():  #  I, P, or S?
                tags[typ] = list(set(tags[typ] + [thes.loc[tok]['alias'].tolist()]))
            else:  # R or X?
                pass # skip'em
        elif np.any([i in vocab_list for i in tok.split(' ')]):
            # If any subset of `tok` is itself a recognized token, skip'em
            pass
        else: # not recognized :(
            untagged += [tok]
    return tags, list(set(untagged))


def tag_corpus(corpus, thes):
    RT, I, S, P, UK = ([], [], [], [], [])

    # make the tf-idf embedding to tokenize with lemma/ngrams
    doc_term_matrix, id2term = textacy.vsm.doc_term_matrix(
            (doc.to_terms_list(ngrams=(1,2,3),
                               normalize=u'lemma',
                               named_entities=False,
#                                filter_stops=True,  # Nope! Not needed :)
                               filter_punct=True,
                               as_strings=True)
                for doc in corpus),
            weighting='tfidf',
            normalize=False,
            smooth_idf=False,
            min_df=2, max_df=0.95)  # each token in >2 docs, <95% of docs
    # iterate over all issues
    for  doc_n, doc in enumerate(tqdm_notebook(corpus)):
        tokens = get_norm_tokens(doc_n, doc_term_matrix, id2term)
        tags, unknown = doc_to_tags(tokens, thes)
        UK += [', '.join(unknown)]
        RT += [doc.text]
        I += [', '.join(tags['I'])]
        S += [', '.join(tags['S'])]
        P += [', '.join(tags['P'])]
    # get back a tagged DF
    return pd.DataFrame(data={
        'RawText': RT,
        'Items': I,
        'Problem': P,
        'Solution': S,
        'UK_tok': UK  # unknown
    }, columns = ['RawText','Items','Problem','Solution','UK_tok'])

df_pred = tag_corpus(corpus, df_vocab)
df_pred.head(10)
```

Out[7]:

	RawText	Items	Problem	Solution	UK_tok
0	Broken bar feeder chain. Repaired	bar, chain, feeder_chain, feeder, bar_feeder, ...	broken	repair	
1	No power. Replaced pin in pendant and powered ...	machine, cable, pendant, pin	short, power	replace	
2	Smartscope harness broken. Parts ordered / Tec...	person, part	broken	repair, order	harness, smartscope
3	Check / Charge Accumulators. Where OK			charge, check	accumulators
4	Hyd leak at saw atachment. Replaced seal in sa...	seal, saw, attachment, hydraulic, saw_attachment	leak	replace	ml
5	CS1008 setup change over / from ARC1004. Compl...	unit, thread, thread_unit		setup, wire, complete, change	
6	Gears on saw attachment tight and grinding per...	shelf, person, attachment, unit, gear	tight	rebuild, see, remove, replace	
7	Check and charge Accumulators. Checked and cha...	accumulator		charge, check	
8	St# 14 milling spindle repairs. Reapired	spindle, milling, st		repair	reapired
9	Hydraulic leak. Replaced ruptured hydraulic li...	hydraulic_line, line, hydraulic	leak, rupture	replace	

- A lot of items are taken care of automatically.
- where "problems" aren't listed, issue is generally routine maintenance.
- **Assumption**: Problem and Solution tags are almost entirely independent sets.
- We get a precise list of what *isn't* known for free...the "Unknowns".

In [8]:
```
# save everything to disk
df_pred.to_excel('keyword_tagged.xlsx')
```

How many have no remaining Unknown Tokens?

i.e. the mapping from token-space (domain) --> tag-space (codomain) is a surjection in the space of this issue

In [9]:
```
df_pred[df_pred.UK_tok ==''].shape[0]
```

Out[9]: 1807

Note that the 3438-1805 = 1633 others *apparently* have extra information to be extracted, or at least, *we cannot be certain that there isn't*.

How many got NO datafication?

i.e. for how many issues was this process completely worthless?

In [10]:
```
# df_pred[df_pred.UK_tok ==''].dropna().shape
print df_pred[(df_pred[['Items','Problem','Solution']]=='').all(axis=1)].shape[0]
df_pred[(df_pred[['Items','Problem','Solution']]=='').all(axis=1)]
```

```
6
```

Out[10]:

	RawText	Items	Problem	Solution	UK_tok
631	Unload automation not returning.				unload, automation
1816	.				
2467	.				
2571	Camshaft standstill. Gary!!				camshaft
3191	Disti water empty. Water filled;				disti, fill
3405	??.				

How well did we do at automating the job of Tagging Issues?

In order to somehow measure our success, we need something to compare with.

Thankfully, some hard-working engineers have gone through and manually tagged over 1200 maintenance issues **by hand**.

We can use these tags as the "gold standard" tags, with which to compare our automated keyword-->tag mapping.

In [11]:
```
df_tag = pd.read_excel(raw_excel_filepath, header=1, encoding=sys.getfilesystemencoding(),
                   names=['Description','Resolution','p_Item','p_Action','s_Action','s_Item'], parse_c
ols=5)
mask = df_tag[['p_Item','p_Action','s_Action','s_Item']].notnull().any(axis=1)

from itertools import chain
from sklearn.preprocessing import MultiLabelBinarizer

human_tags = [list(chain(*[tags.split(', ') for tags in issue[1].values if type(tags)==unicode]))
              for issue in df_tag[['p_Item','p_Action','s_Action','s_Item']][mask].iterrows()]

recog_tags =  [list(chain(*[tags.split(', ') for tags in issue[1].values if type(tags)==unicode]))
              for issue in df_pred[['Items','Problem','Solution']][mask].iterrows()]

print human_tags[0]


multi_bin =  MultiLabelBinarizer().fit(human_tags + recog_tags)
Y_true = multi_bin.transform(human_tags)
print Y_true[0].sum()

Y_train = multi_bin.transform(recog_tags)
```

```
[u'bar_feeder', u'chain', u'bar', u'broken', u'repair', u'bar_feeder', u'chain', u'bar']
5
```

But how will we measure this?

One way is straight-forward and easy to compute...the accuracy. The **accuracy score** measures, on average, how many predicted outputs match the true outputs perfectly:

$$S_A = \frac{1}{n}\sum_{i=1}^{n} 1(T_i = P_i)$$

A better alternative :

This is an *overly-harsh metric* for the performance of multilabel classification, since it ignores *how close* we got to the correct output in each case. The **hamming score** is a more forgiving and/or useful metric:

$$S_H = \frac{1}{n}\sum_{i=1}^{n}\frac{|T_i \cap P_i|}{|T_i \cup P_i|}$$

Note that the closely related **hamming loss** is similar to a distance metric, which unlike the others here is *better when low*.

Interpretability, please:

Finally, we can use the slightly more intuitive **precision**, **recall**, and their harmonic mean F_1**-score**. As put by Scikit-Learn:

> Intuitively, *precision* is the ability of the classifier *not to label as positive a sample that is negative*, and *recall* is the ability of the classifier *to find all the positive samples*.

Then, we can get some sort of combination that balances the two, embodied by F_1. Or, put formally:

$$Pr = \frac{1}{n}\sum_{i=1}^{n}\frac{|T_i \cap P_i|}{|P_i|}$$

$$Re = \frac{1}{n}\sum_{i=1}^{n}\frac{|T_i \cap P_i|}{|T_i|}$$

$$F_1 = \frac{1}{n}\sum_{i=1}^{n}\frac{2Pr_iRe_i}{Pr_i + Re_i}$$

If we want to model some difference between our importance of recall vs. precision, the generalized F-score is defined as:

$$F_\beta = \frac{1}{n}\sum_{i=1}^{n}(1+\beta^2)\frac{Pr_iRe_i}{\beta^2 Pr_i + Re_i}$$

From Van Rijsbergen, this is defined so that F_β:

> "measures the effectiveness of retrieval with respect to a user who attaches β times as much importance to recall as precision".

In our case, Since we do not really trust that the original tags given by humans were all-inclusive (i.e. they might have left out tags below some un-known relevance threshold determined by their attention [read: boredom] level), we want to place more importance on recall in our F-measure. We'll use the commonly-applied F_2

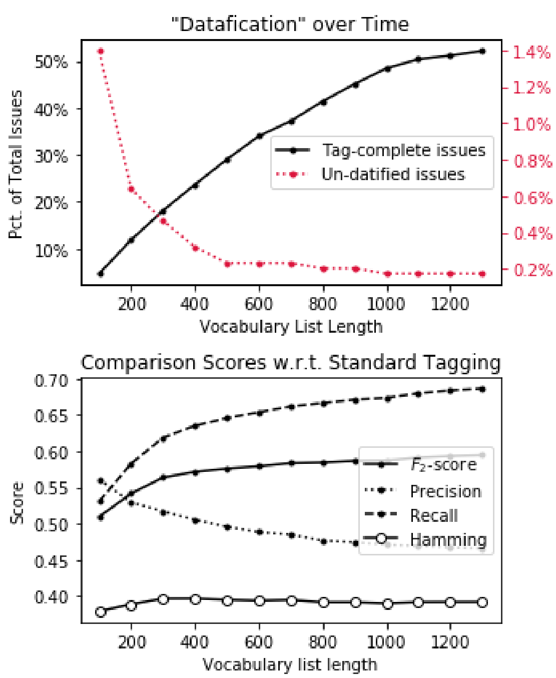
In [12]:
```
from sklearn.metrics import hamming_loss, accuracy_score, precision_recall_fscore_support
from scipy.stats import hmean  # harmonic mean

def hamming_score(y_true, y_pred, normalize=True, sample_weight=None):
    '''
    Compute the Hamming score (a.k.a. label-based accuracy) for the multi-label case
    http://stackoverflow.com/q/32239577/395857
    '''
    acc_list = []
    for i in range(y_true.shape[0]):
        set_true = set( np.where(y_true[i])[0] )
        set_pred = set( np.where(y_pred[i])[0] )
        #print('\nset_true: {0}'.format(set_true))
        #print('set_pred: {0}'.format(set_pred))
        tmp_a = None
        if len(set_true) == 0 and len(set_pred) == 0:
            tmp_a = 1
        else:
            tmp_a = len(set_true.intersection(set_pred))/\
                    float( len(set_true.union(set_pred)) )
```

```
        #print('tmp_a: {0}'.format(tmp_a))
        acc_list.append(tmp_a)
    return np.mean(acc_list)

def f_score(y_true, y_pred, beta=1.):
    '''
    Compute the Precision, Recall, and F-beta Score for the multi-label case
    http://stackoverflow.com/q/32239577/395857
    '''
    fsc_list = []
    pre_list = []
    rec_list = []
    for i in range(y_true.shape[0]):
        set_true = set( np.where(y_true[i])[0] )
        set_pred = set( np.where(y_pred[i])[0] )
        #print('\nset_true: {0}'.format(set_true))
        #print('set_pred: {0}'.format(set_pred))
        tmp_a = None
        if len(set_true) == 0 and len(set_pred) == 0:
            tmp_p, tmp_r, tmp_f = 1, 1, 1
        elif len(set_true.intersection(set_pred)) ==0:
            tmp_p = 0
            tmp_r = 0
            tmp_f = 0
        else:
            tmp_p = len(set_true.intersection(set_pred))/\
                    float( len(set_pred) )
            tmp_r = len(set_true.intersection(set_pred))/\
                    float( len(set_true) )
            try:
                tmp_f = ((1.+beta**2)*tmp_p*tmp_r)/((beta**2)*tmp_p + tmp_r)
            except ValueError:
                print tmp_p, tmp_r
                raise
        #print('tmp_a: {0}'.format(tmp_a))
        pre_list.append(tmp_p)
        rec_list.append(tmp_r)
        fsc_list.append(tmp_f)
    return np.array(pre_list), np.array(rec_list), np.array(fsc_list)

print '---Automatic Keyword Tagging (TF-IDF+human) ---'
print 'Accuracy Score: \t {:.2%}\nHamming Score: \t {:.2%}\nHamming Loss: \t {:.2e}'.format(accuracy_s
core(Y_true, Y_train),
                                                                          hamming_score(Y_true, Y_trai
n),
                                                                          hamming_loss(Y_true,
Y_train))

beta=2

print '\nPrecision: \t {:.2%}\nRecall: \t {:.2%}\nF{beta} Score: \t {:.2%}'.format(
    *[np.mean(i) for i in f_score(Y_true, Y_train, beta=beta)], beta=beta
)
# print '\nPrecision: \t {:.2%}\nRecall: \t {:.2%}\nF1 Score: \t {:.2%}'.format(
#     *[np.mean(i) for i in precision_recall_fscore_support(Y_true, Y_train)[:-1]]
# )
```

```
---Automatic Keyword Tagging (TF-IDF+human) ---
Accuracy Score:          1.82%
Hamming Score:   39.15%
Hamming Loss:    3.44e-03

Precision:       46.47%
Recall:          68.72%
F2 Score:        59.48%
```

In [91]:
```
case_study = []
for n_vocab in tqdm_notebook(np.arange(100,1400, 100)):
    res = {}
    res['df'] = tag_corpus(corpus, df_vocab.iloc[:n_vocab])
    res['n_complete'] = res['df'][res['df'].UK_tok ==''].shape[0]
    res['n_empty'] = res['df'][(res['df'][['Items','Problem','Solution']]=='').all(axis=1)].shape[0]

    recog_tags =  [list(chain(*[tags.split(', ') for tags in issue[1].values if type(tags)==unicode]))

                   for issue in res['df'][['Items','Problem','Solution']][mask].iterrows()]
    multi_bin =  MultiLabelBinarizer().fit(human_tags + recog_tags)
    Y_true = multi_bin.transform(human_tags)
    Y_train = multi_bin.transform(recog_tags)

    res['hamming'] = hamming_score(Y_true, Y_train)
    res['FPR_2'] = f_score(Y_true, Y_train, beta=2)

    case_study += [res]
```

In [163]:
```
f,ax = plt.subplots(nrows=2, figsize=(5,6))
tagged = ax[0].plot(np.arange(100,1400, 100),
         np.array([i['n_complete'] for i in case_study])/float(df_pred.shape[0]),
           label='Tag-complete issues', c='k', marker='.')
ax2 = ax[0].twinx()
untag = ax2.plot(np.arange(100,1400, 100),
         np.array([i['n_empty'] for i in case_study])/float(df_pred.shape[0]),
         label = "Un-datified issues", marker='.', c='crimson', ls=':')

lns = tagged + untag
labs = [l.get_label() for l in lns]
ax[0].legend(lns, labs, loc='center right')
ax2.tick_params(axis='y', colors='crimson')

ax[0].set_ylabel('Pct. of Total Issues')
ax[0].set_xlabel('Vocabulary List Length')
ax[0].set_title('"Datafication" over Time')
# ax[0].legend(, loc=0)

vals = ax[0].get_yticks()
ax[0].set_yticklabels(['{:.0%}'.format(x) for x in vals])
vals = ax2.get_yticks()
ax2.set_yticklabels(['{:.1%}'.format(x) for x in vals])

ax[1].plot(np.arange(100,1400, 100),
         [i['FPR_2'][2].mean() for i in case_study], label=u'$F_2$-score', c='k',marker='.')
ax[1].plot(np.arange(100,1400, 100),
         [i['FPR_2'][0].mean() for i in case_study], label='Precision', c='k', ls=':',marker='.')
ax[1].plot(np.arange(100,1400, 100),
         [i['FPR_2'][1].mean() for i in case_study], label='Recall', c='k', ls='--',marker='.')

ax[1].plot(np.arange(100,1400, 100),
         [i['hamming'] for i in case_study], label='Hamming', ls='-',marker='o', c='k', markerfacecolo
r='white')
ax[1].legend(loc='center right')
ax[1].set_ylabel('Score')
ax[1].set_xlabel('Vocabulary list length')
ax[1].set_title('Comparison Scores w.r.t. Standard Tagging')

plt.tight_layout()
plt.savefig('study.png')
```



Using Machine Learning (SVM + Word2Vec)

Benchmarking the auto-tagger

Is there another way?

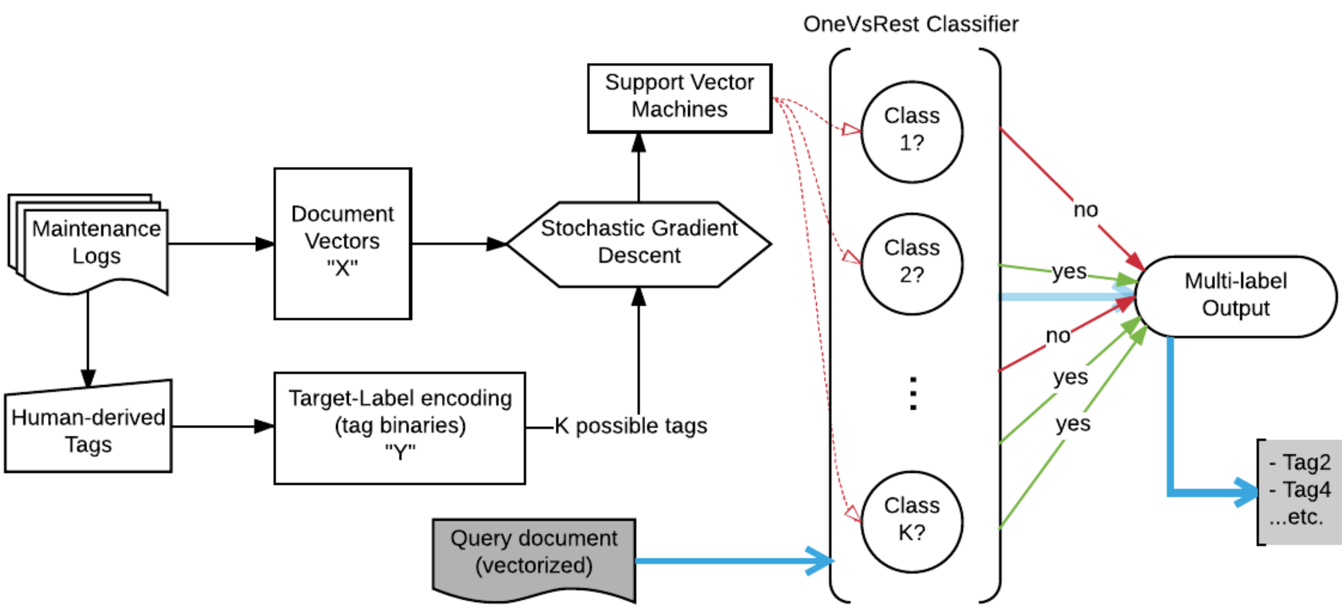
Now, it's important to note that all of the above was done **only** with a list of categorized keywords (i.e. some mapping from token-space to tag-space), and creating that mapping did not at all depend upon some human having tagged *individual issues* already...we were just using those tagged issues as a scoring/benchmark tool.

If we approach this as a classification problem, assuming these tagged issues *do exist*, we might attempt to train a classifier to predict the set of tags appropriate for given **raw-english** input.

Let's try this:

- first a mapping from token-space to some useful vector-space (could be tf-idf, maybe a topic model, but here we will use the shiny new **Word2Vec** semantic embedding vectors of our corpus, courtesy of Google+Textacy/Spacy).
- Then we will train a **classifier** to exactly match the **Multilabel** output, represented by the individual human-tagged issues.

Support-vector-machines work amazingly well on text embedding classification jobs, so let's use a linear SVC trained using stochasic gradient descent (SGD) via sklearn. We should also minimize overfitting with this hugely dimensional job, so we'll regularize with an elasticnet penalty (L1+L2).



```
from sklearn.multiclass import OneVsRestClassifier
from sklearn.linear_model import SGDClassifier

X_train = corpus.vectors[mask]
clf = OneVsRestClassifier(SGDClassifier(#class_weight='balanced',  # compensate for class freqs
                                        penalty='elasticnet'   # L1 + L2 regularized
                                        ), n_jobs=3  # 3-cores for the one-vs-all
                         )
clf.fit(X_train, Y_true)
Y_train_w2v = clf.predict(X_train)
```

In [13]:
```
from sklearn.multiclass import OneVsRestClassifier
from sklearn.linear_model import SGDClassifier

X_train = corpus.vectors[mask]
clf = OneVsRestClassifier(SGDClassifier(#class_weight='balanced',  # compensate for class freqs
                                        penalty='elasticnet'   # L1 + L2 regularized
                                        ), n_jobs=3  # 3-cores for the one-vs-all
                         )
clf.fit(X_train, Y_true)
Y_train_w2v = clf.predict(X_train)
```

In [14]:
```
print '---W2V Embeddings with SVC (OneVsRest, SGD)---'
print 'Accuracy Score: \t {:.2%}\nHamming Score: \t {:.2%}\nHamming Loss: \t {:.2e}'.format(accuracy_s
core(Y_true, Y_train_w2v),
                                                                                             hamming_score(Y_true, Y_trai
n_w2v),
                                                                                             hamming_loss(Y_true, Y_train
_w2v))
beta=2
print '\nPrecision: \t {:.2%}\nRecall: \t {:.2%}\nF{beta} Score: \t {:.2%}'.format(
    *[np.mean(i) for i in f_score(Y_true, Y_train_w2v, beta=beta)], beta=beta
)
# print '\nPrecision: \t {:.2%}\nRecall: \t {:.2%}\nF1 Score: \t {:.2%}'.format(
#     *[np.mean(i) for i in precision_recall_fscore_support(Y_true, Y_train_w2v)[:-1]]
# )
```

```
---W2V Embeddings with SVC (OneVsRest, SGD)---
Accuracy Score:          16.70%
Hamming Score:   55.36%
Hamming Loss:    1.93e-03

Precision:       73.50%
Recall:          69.13%
F2 Score:        67.03%
```

In [15]:
```
# from __future__ import print_function
from ipywidgets import interact, interactive
import ipywidgets as widgets
from IPython.display import display

def compare_by_issue(iss):
    print 'Issue No. ',iss
    print df_pred[mask]['RawText'].iloc[iss]
    print '\nHuman-tagged \"True\" Keyworks/Tags: \t{}'.format(', '.join(sorted(multi_bin.inverse_tran
sform(Y_true)[iss])))

    print '\nTF-IDF rank Human-classified keywords: \t{}'.format(', '.join(sorted(multi_bin.inverse_tr
ansform(Y_train)[iss])))
    print 'Precision: \t {:.2%}\nRecall: \t {:.2%}\nF2 Score: \t {:.2%}'.format(
        *[i[iss] for i in f_score(Y_true, Y_train, beta=2.)]
    )
    print '\nWord2Vec + SVM Multilabel Classifier: \t{}'.format(', '.join(sorted(multi_bin.inverse_tra
nsform(Y_train_w2v)[iss])))
    print 'Precision: \t {:.2%}\nRecall: \t {:.2%}\nF2 Score: \t {:.2%}'.format(
        *[i[iss] for i in f_score(Y_true, Y_train_w2v, beta=2.)]
    )
# compare_by_issue(0)
```

Wow, that's pretty fantastic, considering the task we've set before it! Better performance, at least on a per-metric level, than our automated keyword-tagger in every way!

Still, note that the precision is almost 80%...this may or may not be a model we want to actually use early on, given that we may or may not trust our engineers' tagging job. Assuming We 100% trust the keyword flagger when it recognizes a word, the precision of that one is actually 100%, and any discrepancy is on the part of *the original tags*.

Another way to look at it is our keyword tagger is being really nit-picky and overly-accurate, which precision is punishing. Our classifier, on the other hand, is being trained *to tag like the humans*.

Let's dig in a bit.. To get a more fine-grained idea of what's going on, we can also look at the Pr/Re/F scores on an individual-issue level to get a better idea of the performance of each model.

In [16]:
```
interact(compare_by_issue, iss=widgets.BoundedIntText(
                    value=0,
                    min=0,
                    max=3437,
                    description='Pick an Issue No.:',
                    step=1
                    )
               );
# display(w)
```

Analysis

Now that we have tags, what do we do with them?

- **MaxLikelihood Example Demo**
- **Something simpler?**

First let's get some of the most common tags and convert them into binary indicators on a per-issue basis.

In [17]:
```python
def get_relevant(df, col, topn=20):

    tags = [x[1][col].split(', ') for x in df.iterrows()]
    binner = MultiLabelBinarizer().fit(tags)
    vecs = binner.transform(tags)
    counts = vecs.sum(axis=0)
    relevant = [(binner.classes_[i], counts[i], vecs[:,i]) for i in counts.argsort()[-topn:][::-1]]
    return relevant

relevant = get_relevant(df_pred, 'Items', topn=20) +\
get_relevant(df_pred, 'Problem', topn=20) +\
get_relevant(df_pred, 'Solution', topn=20)
print 'e.g. ...'
relevant[:10]
```

```
e.g. ...
```

Out[17]:
```
[(u'unit', 366, array([0, 0, 0, ..., 0, 0, 0])),
 (u'spindle', 297, array([0, 0, 0, ..., 0, 0, 0])),
 (u'hydraulic', 275, array([0, 0, 0, ..., 0, 1, 1])),
 (u'motor', 247, array([0, 0, 0, ..., 0, 0, 0])),
 (u'valve', 234, array([0, 0, 0, ..., 0, 0, 1])),
 (u'bar', 232, array([1, 0, 0, ..., 0, 0, 0])),
 (u'machine', 205, array([0, 1, 0, ..., 0, 0, 0])),
 (u'accumulator', 204, array([0, 0, 0, ..., 0, 0, 0])),
 (u'coolant', 197, array([0, 0, 0, ..., 0, 0, 0])),
 (u'person', 188, array([0, 0, 1, ..., 0, 0, 0]))]
```

In [18]:
```python
# item_counts = Item_vecs.sum(axis=0)
# relevant = [(binner.classes_[i], item_counts[i], Item_vecs[:,i]) for i in item_counts.argsort()[-2
0:][::-1]]
event_df = pd.DataFrame(columns = [i[0] for i in relevant if i[0]!=u''],
             data = np.array([i[2] for i in relevant if i[0]!=u'']).T)
# plt.barh()
event_df.head(10)
```

Out[18]:

	unit	spindle	hydraulic	motor	valve	bar	machine	accumulator	coolant	person	...	reset	charge	clear	swap
0	0	0	0	0	0	1	0	0	0	0	...	0	0	0	0
1	0	0	0	0	0	0	1	0	0	0	...	0	0	0	0
2	0	0	0	0	0	0	0	0	0	1	...	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	...	0	1	0	0
4	0	0	1	0	0	0	0	0	0	0	...	0	0	0	0
5	1	0	0	0	0	0	0	0	0	0	...	0	0	0	0
6	1	0	0	0	0	0	0	0	0	1	...	0	0	0	0
7	0	0	0	0	0	0	0	1	0	0	...	0	1	0	0
8	0	1	0	0	0	0	0	0	0	0	...	0	0	0	0
9	0	0	1	0	0	0	0	0	0	0	...	0	0	0	0

10 rows × 58 columns

Now we want to get other information, say, the *time* a problem was submitted.

In [19]:
```
# og_data_loc = os.path.join(data_directory, 'Maintenance_All_Clean.xlsx')
og_data = pd.read_excel(raw_excel_filepath,header=1, parse_dates=True, index_col='DATE RECEIVED')
                        #[['DATE RECEIVED','Time Submitted']])
# og_data.set_index('DATE RECEIVED_Time Submitted', inplace=True)
# og_data.set_index('DATE RECEIVED', inplace=True)

# print og_data.iloc[1381]
og_data.head()
```

Out[19]:

	Description	Resolution	Item Tags	Action Tags	Action Tags.1	Item Tags.1	Unna 6
DATE RECEIVED							
2015-01-11	Broken bar feeder chain	Repaired	bar_feeder, chain, bar	broken	repair	bar_feeder, chain, bar	NaN
2015-01-14	No power	Replaced pin in pendant and powered machine - P...	pendant_cable, cable	short, no_power	replace	pin	NaN
2015-02-27	Smartscope harness broken	Parts ordered / Tech repaired	smartscope_harness	broken	order, repair	smartscope_harness	NaN
2015-02-27	Check / Charge Accumulators	Where OK	accumulator	check, charge	no_problem_detected	NaN	NaN
2015-02-27	Hyd leak at saw atachment	Replaced seal in saw attachment but still leak...	hydraulic, saw_attachment, saw	leak	replace, need_guy	seal	NaN

and then, re-index our indicator items.

In [20]:
```
df_raw.head()
event_df.index = og_data.index
event_df.index = pd.to_datetime(event_df.index, errors='coerce')
event_df.iloc[2500:2505]
```

Out[20]:

	unit	spindle	hydraulic	motor	valve	bar	machine	accumulator	coolant	person	...	reset	charge	cle
DATE RECEIVED														
2016-08-01	0	0	1	0	0	0	0	0	0	0	...	0	0	0
2016-08-01	0	1	0	0	0	0	0	0	0	0	...	0	0	0
2016-08-01	0	0	0	0	0	0	0	0	0	0	...	0	0	0
2016-08-01	0	0	0	0	0	0	0	0	0	0	...	0	0	0
2016-08-01	0	0	0	0	0	0	0	0	1	0	...	1	0	1

5 rows × 58 columns

In [21]:
```
"""
Calendar heatmaps from Pandas time series data.
Plot Pandas time series data sampled by day in a heatmap per calendar year,
similar to GitHub's contributions calendar.

adapted from:
    'Martijn Vermaat' 14 Feb 2016
    'martijn@vermaat.name'
    'https://github.com/martijnvermaat/calmap'
"""
from __future__ import unicode_literals

import calendar
import datetime

from matplotlib.colors import ColorConverter, ListedColormap
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from distutils.version import StrictVersion

_pandas_18 = StrictVersion(pd.__version__) >= StrictVersion('0.18')


def yearplot(data, year=None, how='sum', vmin=None, vmax=None, cmap='Reds',
             fillcolor='whitesmoke', linewidth=1, linecolor=None,
             daylabels=calendar.day_abbr[:], dayticks=True,
             monthlabels=calendar.month_abbr[1:], monthticks=True, ax=None,
             **kwargs):
    """
    Plot one year from a timeseries as a calendar heatmap.
    Parameters
    ----------
    data : Series
        Data for the plot. Must be indexed by a DatetimeIndex.
    year : integer
        Only data indexed by this year will be plotted. If `None`, the first
        year for which there is data will be plotted.
    how : string
        Method for resampling data by day. If `None`, assume data is already
        sampled by day and don't resample. Otherwise, this is passed to Pandas
        `Series.resample`.
    vmin, vmax : floats
        Values to anchor the colormap. If `None`, min and max are used after
        resampling data by day.
    cmap : matplotlib colormap name or object
        The mapping from data values to color space.
    fillcolor : matplotlib color
        Color to use for days without data.
    linewidth : float
        Width of the lines that will divide each day.
    linecolor : color
        Color of the lines that will divide each day. If `None`, the axes
        background color is used, or 'white' if it is transparent.
    daylabels : list
        Strings to use as labels for days, must be of length 7.
    dayticks : list or int or bool
        If `True`, label all days. If `False`, don't label days. If a list,
        only label days with these indices. If an integer, label every n day.
    monthlabels : list
        Strings to use as labels for months, must be of length 12.
    monthticks : list or int or bool
        If `True`, label all months. If `False`, don't label months. If a
        list, only label months with these indices. If an integer, label every
        n month.
    ax : matplotlib Axes
        Axes in which to draw the plot, otherwise use the currently-active
        Axes.
    kwargs : other keyword arguments
        All other keyword arguments are passed to matplotlib `ax.pcolormesh`.
    Returns
```

```
    -------
    ax : matplotlib Axes
        Axes object with the calendar heatmap.
    Examples
    --------
    By default, `yearplot` plots the first year and sums the values per day:
    .. plot::
        :context: close-figs
        calmap.yearplot(events)
    We can choose which year is plotted with the `year` keyword argment:
    .. plot::
        :context: close-figs
        calmap.yearplot(events, year=2015)
    The appearance can be changed by using another colormap. Here we also use
    a darker fill color for days without data and remove the lines:
    .. plot::
        :context: close-figs
        calmap.yearplot(events, cmap='YlGn', fillcolor='grey',
                        linewidth=0)
    The axis tick labels can look a bit crowded. We can ask to draw only every
    nth label, or explicitely supply the label indices. The labels themselves
    can also be customized:
    .. plot::
        :context: close-figs
        calmap.yearplot(events, monthticks=3, daylabels='MTWTFSS',
                        dayticks=[0, 2, 4, 6])
    """
    if year is None:
        year = data.index.sort_values()[0].year

    if how is None:
        # Assume already sampled by day.
        by_day = data
    else:
        # Sample by day.
        if _pandas_18:
            by_day = data.resample('W').agg(how)
        else:
            by_day = data.resample('W', how=how)

    # Min and max per day.
    if vmin is None:
        vmin = by_day.min().min()
    if vmax is None:
        vmax = by_day.max().max()

    if ax is None:
        ax = plt.gca()

    if linecolor is None:
        # Unfortunately, linecolor cannot be transparent, as it is drawn on
        # top of the heatmap cells. Therefore it is only possible to mimic
        # transparent lines by setting them to the axes background color. This
        # of course won't work when the axes itself has a transparent
        # background so in that case we default to white which will usually be
        # the figure or canvas background color.
        linecolor = ax.get_axis_bgcolor()
        if ColorConverter().to_rgba(linecolor)[-1] == 0:
            linecolor = 'white'

    # Filter on year.
    by_day = by_day[by_day.index.year==year]

    # Add missing days.

    plot_data = by_day.transpose().fillna(0)

    # Draw heatmap.
    kwargs['linewidth'] = linewidth
    kwargs['edgecolors'] = linecolor
    ax.pcolormesh(plot_data, vmin=vmin, vmax=vmax, cmap=cmap, **kwargs)
    # Limit heatmap to our data.
```

```
    ax.set(xlim=(0, plot_data.shape[1]), ylim=(0, plot_data.shape[0]))

    # Square cells.
    ax.set_aspect('equal')

    # Remove spines and ticks.
    for side in ('top', 'right', 'left', 'bottom'):
        ax.spines[side].set_visible(False)
    ax.xaxis.set_tick_params(which='both', length=0)
    ax.yaxis.set_tick_params(which='both', length=0)

    # Get indices for monthlabels.
    if monthticks is True:
        monthticks = range(len(monthlabels))
    elif monthticks is False:
        monthticks = []
    elif isinstance(monthticks, int):
        monthticks = range(len(monthlabels))[monthticks // 2::monthticks]

    # Get indices for daylabels.
    if dayticks is True:
        dayticks = range(len(daylabels))
    elif dayticks is False:
        dayticks = []
    elif isinstance(dayticks, int):
        dayticks = range(len(daylabels))[dayticks // 2::dayticks]
    ax.set_xlabel('')
    ax.set_xticklabels([monthlabels[i] for i in monthticks], ha='center')

    ax.set_xticks([pd.Timestamp('{}/15/{}'.format(i, year)).week-1.5 for i in range(1,13)])
    ax.set_ylabel('')
    ax.yaxis.set_ticks_position('right')
    ax.set_yticks([by_day.columns.shape[0] - i - .5  for i in range(by_day.columns.shape[0])])
    ax.set_yticklabels(by_day.columns[::-1], rotation='horizontal',
                       va='center')

    return ax

def calendarplot(data, how='sum', yearlabels=True, yearascending=True, yearlabel_kws=None,
                 subplot_kws=None, gridspec_kws=None, fig_kws=None, **kwargs):
    """
    Plot a timeseries as a calendar heatmap.
    Parameters
    ----------
    data : Series
        Data for the plot. Must be indexed by a DatetimeIndex.
    how : string
        Method for resampling data by day. If `None`, assume data is already
        sampled by day and don't resample. Otherwise, this is passed to Pandas
        `Series.resample`.
    yearlabels : bool
       Whether or not to draw the year for each subplot.
    yearascending : bool
       Sort the calendar in ascending or descending order.
    yearlabel_kws : dict
       Keyword arguments passed to the matplotlib `set_ylabel` call which is
       used to draw the year for each subplot.
    subplot_kws : dict
        Keyword arguments passed to the matplotlib `add_subplot` call used to
        create each subplot.
    gridspec_kws : dict
        Keyword arguments passed to the matplotlib `GridSpec` constructor used
        to create the grid the subplots are placed on.
    fig_kws : dict
        Keyword arguments passed to the matplotlib `figure` call.
    kwargs : other keyword arguments
        All other keyword arguments are passed to `yearplot`.
    Returns
    -------
    fig, axes : matplotlib Figure and Axes
        Tuple where `fig` is the matplotlib Figure object `axes` is an array
        of matplotlib Axes objects with the calendar heatmaps, one per year.
```

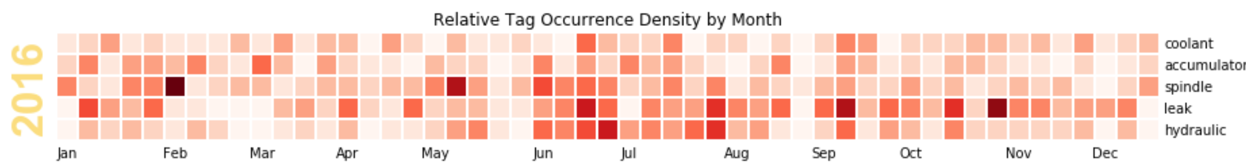
```
    Examples
    --------
    With `calendarplot` we can plot several years in one figure:
    .. plot::
        :context: close-figs
        calmap.calendarplot(events)
    """
    yearlabel_kws = yearlabel_kws or {}
    subplot_kws = subplot_kws or {}
    gridspec_kws = gridspec_kws or {}
    fig_kws = fig_kws or {}

    years = np.unique(data.index.year)
    if not yearascending:
        years = years[::-1]

    fig, axes = plt.subplots(nrows=len(years), ncols=1, squeeze=False,
                             subplot_kw=subplot_kws,
                             gridspec_kw=gridspec_kws, **fig_kws)
    axes = axes.T[0]

    # We explicitely resample by day only once. This is an optimization.
    if how is None:
        by_day = data
    else:
        if _pandas_18:
            by_day = data.resample('W').agg(how)
        else:
            by_day = data.resample('W', how=how)

    ylabel_kws = dict(
        fontsize=32,
        color=kwargs.get('fillcolor', 'xkcd:wheat'),
        fontweight='bold',
        fontname='Arial',
        ha='center')
    ylabel_kws.update(yearlabel_kws)

    max_weeks = 0

    for year, ax in zip(years, axes):
        yearplot(by_day, year=year, how=None, ax=ax, **kwargs)
        max_weeks = max(max_weeks, ax.get_xlim()[1])

        if yearlabels:
            ax.set_ylabel(str(year), **ylabel_kws)

    # In a leap year it might happen that we have 54 weeks (e.g., 2012).
    # Here we make sure the width is consistent over all years.
    for ax in axes:
        ax.set_xlim(0, max_weeks)

    # Make the axes look good.
    plt.tight_layout()

    return fig, axes
```

Let's pick a few interesting items, and see how often they come up as a problem/solution:

In [168]:
```python
# plt.figure
calendarplot(event_df[['hydraulic',
                        'leak',
                        'spindle',
                        'accumulator',
                        'coolant'
                        ]][event_df.index.year==2016],
             how='sum', fig_kws={'figsize':(13,9)});
plt.title('Relative Tag Occurrence Density by Month')
# yearplot(event_df[['hydraulic', 'spindle','accumulator', 'operator']], how='sum', fig_kws={'figsiz
e':(12,8)})
# og_data[event_df.index.isnull()]
```

```
C:\Users\tbs4\AppData\Local\Continuum\Anaconda2\lib\site-packages\ipykernel\__main__.py:128: Matplotl
ibDeprecationWarning: The get_axis_bgcolor function was deprecated in version 2.0. Use get_facecolor
 instead.
```

Out[168]: <matplotlib.text.Text at 0xc7ff1c50>



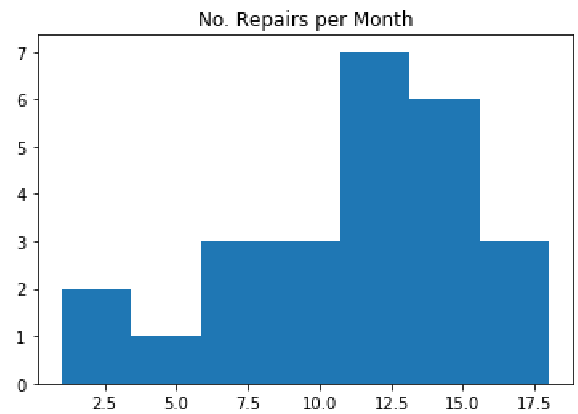
In [23]:
```python
event_df[event_df.operator==1].sum().to_frame(name='operator_incidents').sort_values('operator_inciden
ts',

ascending=False).iloc[:10]
```

Out[23]:

	operator_incidents
operator	162
level	67
train_operator	64
replace	32
fault	29
loose	26
bar	20
broken	20
machine	19
remove	17

In [24]:
```
week_df = event_df.resample('M').agg(sum).fillna(0)
plt.hist(week_df['repair'].values, bins='auto')
plt.title('No. Repairs per Month')
```

Out[24]: `<matplotlib.text.Text at 0xacacd9b0>`



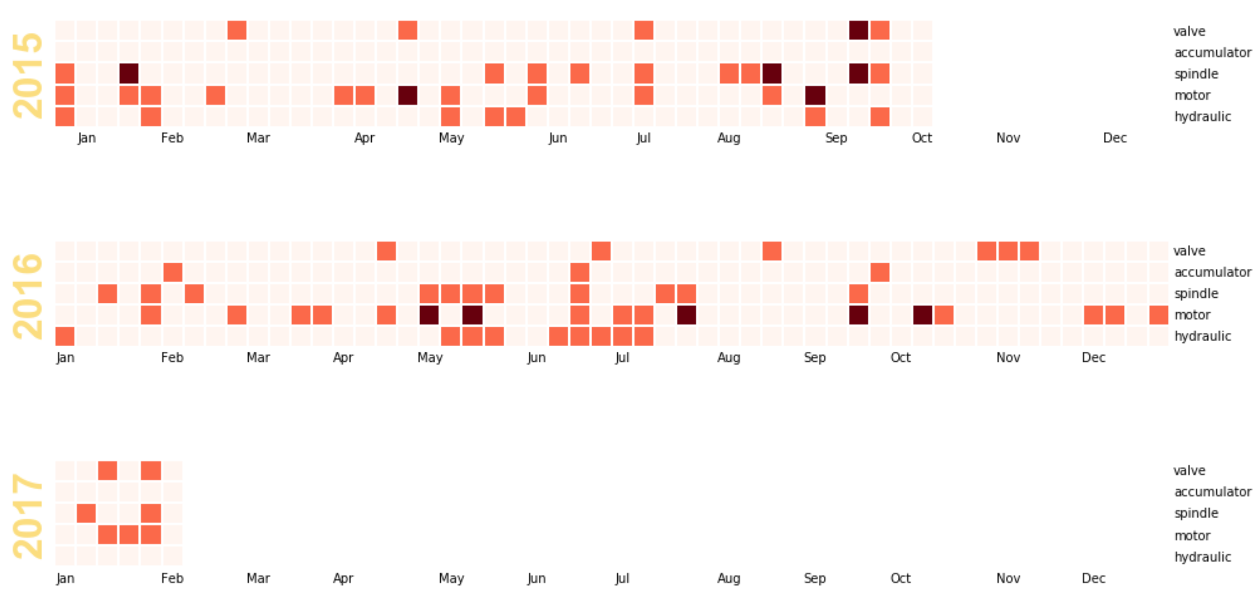
Beginning of Prognostics

We need to approximate the idea of "machine failure" as opposed to "machine maintenance" (compare to "patient care" vs. "patient death".

One way is to only find items occuring with "broken" **AND** "replace". While not 100% accurate, it's definitely a quick and dirty way to estimate the failure rate.

In [25]:
```
weekly_replace = event_df[(event_df['broken']==1) & (event_df['replace']==1)].resample('W').agg(sum).f
illna(0)
calendarplot(weekly_replace[['hydraulic',
                             'motor',
                             'spindle',
                             'accumulator',
                             'valve'
                            ]],
             fig_kws={'figsize':(14,8)});
```

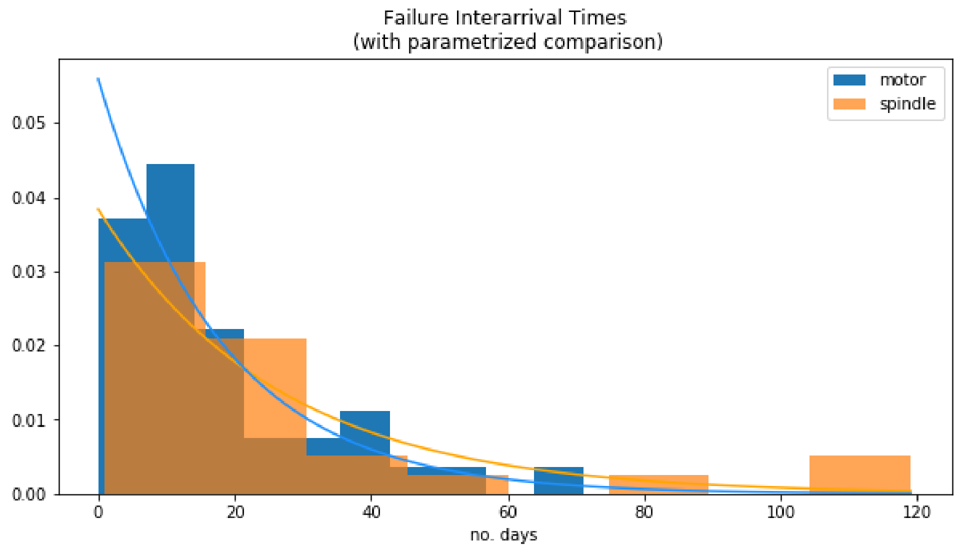
```
C:\Users\tbs4\AppData\Local\Continuum\Anaconda2\lib\site-packages\ipykernel\__main__.py:128: Matplotl
ibDeprecationWarning: The get_axis_bgcolor function was deprecated in version 2.0. Use get_facecolor
 instead.
```



In [26]:
```
from scipy.stats import norm, expon
def get_fail_iat(event_df, tag):
    fail_time_valve = event_df[(event_df['broken']==1) & (event_df['replace']==1) &
(event_df[tag]==1)]
    fail_time_valve['date']=fail_time_valve.index
    fail_time_valve.index = range(fail_time_valve.shape[0])
    iat_valve = fail_time_valve['date']-fail_time_valve.shift()['date']
    return iat_valve

plt.figure(figsize=(10,5))
plt.hist((get_fail_iat(event_df, 'motor')/ pd.Timedelta(days=1)).values[1:], label='motor',
                                                              normed=True)
plt.title('Failure Interarrival Times\n (with parametrized comparison)')
plt.xlabel('no. days')

plt.hist((get_fail_iat(event_df, 'spindle')/ pd.Timedelta(days=1)).values[1:], label='spindle',
                                                                alpha=.7, normed=True, bins='auto')
# plt.title('Motor Failure\n Interarrival Times')
# plt.xlabel('no. days')
plt.legend()
print 'expected interarrival time'
print 'spindle fail:\t{:.2f} days'.format((get_fail_iat(event_df, 'spindle')/ pd.Timedelta(days=1)).me
an())
plt.plot(range(120), expon(scale=(get_fail_iat(event_df, 'spindle')/
pd.Timedelta(days=1)).mean()).pdf(np.arange(120)),
        color='orange')

print 'motor fail:\t{:.2f} days'.format((get_fail_iat(event_df, 'motor')/
pd.Timedelta(days=1)).mean())
plt.plot(range(120), expon(scale=(get_fail_iat(event_df, 'motor')/ pd.Timedelta(days=1)).mean()).pdf(n
p.arange(120)),
        color='dodgerblue')
plt.grid(b=False)
```

```
C:\Users\tbs4\AppData\Local\Continuum\Anaconda2\lib\site-packages\ipykernel\__main__.py:4: SettingWit
hCopyWarning:
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-docs/stable/indexing.html#index
ing-view-versus-copy
```

```
expected interarrival time
spindle fail:   26.08 days
motor fail:     17.89 days
```



Taxonomy Generation

It would be great if we had organized all of these tags, determining which ones are more general or specific.

It would be even better if we had a starting point to do that, done for us.

Graph Theory I

Retrieving those same binary vectors for the top Items, lets call them $\mathbf{B}$. What we want is an idea of how many times particular tags happen together.

Luckily, this is $B^T B$

In [28]:
```
itm_relevant = get_relevant(df_pred, 'Items', topn=500)
itm_event = pd.DataFrame(columns = [i[0] for i in itm_relevant if i[0]!=u''],
             data = np.array([i[2] for i in itm_relevant if i[0]!=u'']).T)
```

In [29]:
```
coocc = itm_event.T.dot(itm_event)
occ = np.diagonal(np.copy(coocc))

np.fill_diagonal(coocc.values, 0)
coocc.head()
```

Out[29]:

	unit	spindle	hydraulic	motor	valve	bar	machine	accumulator	coolant	person	...	clamp_jaw_set	ba
unit	0	30	29	60	16	5	10	8	6	25	...	0	0
spindle	30	0	22	20	24	8	14	2	3	22	...	0	0
hydraulic	29	22	0	23	51	8	12	15	6	15	...	3	1
motor	60	20	23	0	2	1	8	1	22	14	...	0	0
valve	16	24	51	2	0	12	11	9	8	12	...	0	0

5 rows × 499 columns

Actually, $B^T B$ contains the overall occurrence count in it's diagonal. What we are actually using is $B^T B - \mathrm{diag}(B^T B)$, which is called an *adjacency* graph.

Graph Theory II

One way to analyse this is using some notion of **node similarity**. There are a few different ways of measuring the similarity of tags, but one straight-forward one is the ever-popular *cosine similarity*. In the context of co-occurnce graphs, we can caclulate this as

$$\frac{n_{x,y}}{\sqrt{n_x}\sqrt{n_y}}$$

Where n_x, n_y, and $n_{x,y}$ are the number of "issues" or documents tagged with the tag, x, y, or $x \cup y$, respectively. This makes for a nice edge weigting on our cooccurrence graph.

In [30]:
```
dist_mat = coocc/np.dot(np.sqrt(occ).T, np.sqrt(occ))

dist_mat.head()
```

Out[30]:

	unit	spindle	hydraulic	motor	valve	bar	machine	accumulator	coolant	person	...
unit	0.000000	0.002106	0.002035	0.004211	0.001123	0.000351	0.000702	0.000561	0.000421	0.001755	...
spindle	0.002106	0.000000	0.001544	0.001404	0.001684	0.000561	0.000983	0.000140	0.000211	0.001544	...
hydraulic	0.002035	0.001544	0.000000	0.001614	0.003579	0.000561	0.000842	0.001053	0.000421	0.001053	...
motor	0.004211	0.001404	0.001614	0.000000	0.000140	0.000070	0.000561	0.000070	0.001544	0.000983	...
valve	0.001123	0.001684	0.003579	0.000140	0.000000	0.000842	0.000772	0.000632	0.000561	0.000842	...

5 rows × 499 columns

However, this is a symmetric measure, so it doesnt't help us in creating any kind of taxonomy. That's where centrality comes in.

Graph Theory III

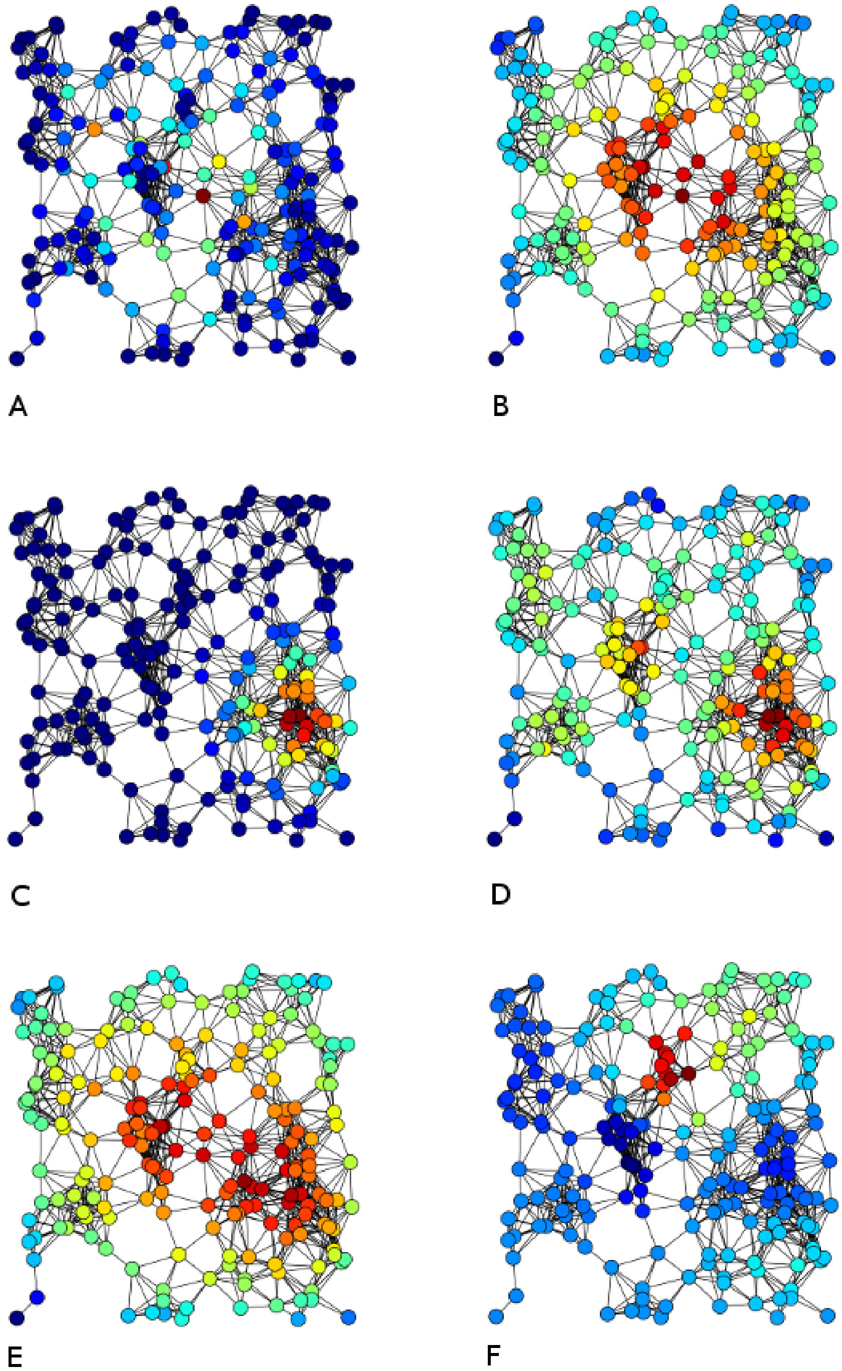
Centrality is a way of rank-ordering nodes according to their "importance" in the graph. There are many ways to formalize this idea, and Google built its business around **PageRank**, a remarkably robust centrality measure.

For example, we have:

```
A.  Betweenness centrality,
B.  Closeness centrality,
C.  Eigenvector centrality,
D.  Degree centrality,
E.  Harmonic Centrality and
F.  Katz centrality
```

of the same graph. (PageRank is related to eigen-centrality)

Now we can combine what we know to make a taxonomy!



In [31]:
```
import networkx as nx

G = nx.from_numpy_matrix(dist_mat.values)
G = nx.relabel_nodes(G, dict(zip(G.nodes(), dist_mat.columns)))
```

In [32]:
```
# cent = pd.Series(nx.closeness_centrality(G, distance='weight'))
# cent = pd.Series(nx.betweenness_centrality(G))
# cent = pd.Series(nx.eigenvector_centrality(G))
cent = pd.Series(nx.pagerank(G))
```

In [33]:
```
cent.sort_values(ascending=False).iloc[:10].index.values
# cent
```

Out[33]:
```
array([u'unit', u'hydraulic', u'bar', u'spindle', u'motor', u'valve',
       u'person', u'machine', u'coolant', u'screw'], dtype=object)
```

Graph Theory IV

The **Heymann** algorithm [Heymann 2006] is an efficient algorithm that converts a set of these "tags" into a taxonomy via "annotation frequencies".

1. List Tags **in order** of generality, which we measure by proxy via **centrality**.
2. **For** each tag in the ordered list (starting with the "most general" node as a root):
   A. **Insert** it as a node
   B. Find the node, already in the taxonomy, **most similar** to it
   C. **If** this similarity is above some **threshold**, add an edge from that node to this on
   D. Else, leave this node as a top-level tag *
3. **Remove** any "isolates", or nodes that have no descendants in the taxonomy.

As a consequence of the similarity threshold, this particular algorithm **removes** any unnecessary and/or **irrelevant tags**.

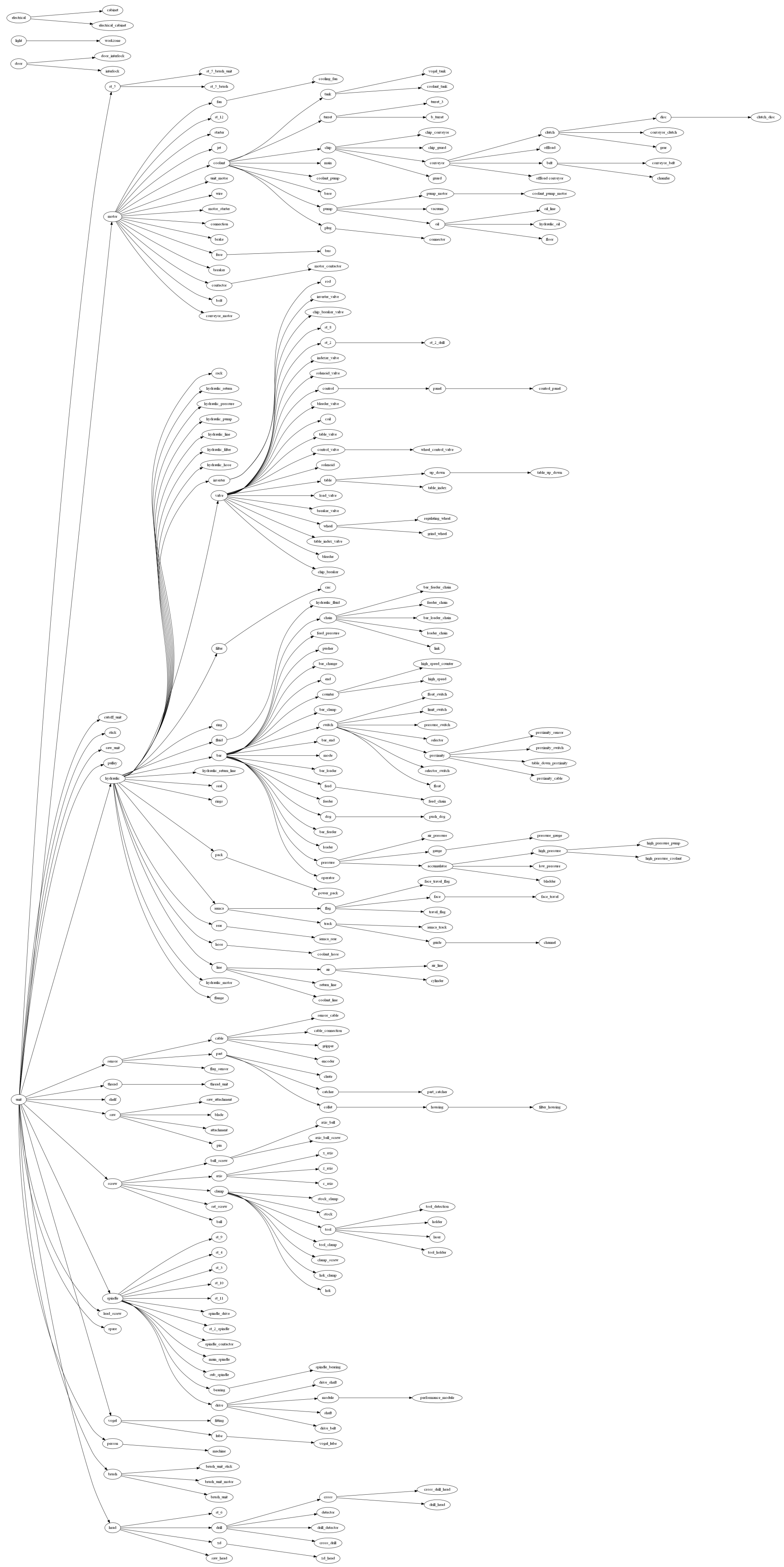
*This is a slight modification, which allows for multiple top-level concepts in the taxonomy.

In [34]:
```
def heymann_taxonomy(dist_mat, cent_prog='pr', tau=5e-4,
                     dynamic=False, dotfile=None, verbose=False):
    """
    dist_mat: dataframe containing similarity matrix, indexed and named by tags
    cent_prog: algorithm to use in calculating node centrality
        pr: PageRank
        eig: eigencentrality
        btw: betweenness
        cls: closeness
    tau: similarity threshold for retaining a node
    dynamic: re-calculate centrality after adding every tag
    write_dot: fname or None, where to save a .dot, if any.
    verbose: print some stuff
    """
#     tau = 5e-4
    cent_dict = {
        'pr': nx.pagerank,
        'eig': nx.eigenvector_centrality,
        'btw': nx.betweenness_centrality,
        'cls': nx.closeness_centrality
    }

    # Create the co-occurence graph, G
    G = nx.from_numpy_matrix(dist_mat.values)
    G = nx.relabel_nodes(G, dict(zip(G.nodes(), dist_mat.columns)))

    # Calculate the centrality of nodes in G
    cent = pd.Series(cent_dict[cent_prog](G)).sort_values(ascending=False)
    root = cent.index[0]

    # Init the taxonomy D (DAG)
    D = nx.DiGraph()
    D.add_node(root)

    for n in tqdm_notebook(range(dist_mat.shape[0])):

        # Pick the most central node in G, and the node in D most similar to it
        tag = cent.index[0]
        neighbor_sim =  {k: dist_mat.loc[tag,k] for k in D.nodes()}
        parent = max(neighbor_sim, key=lambda key: neighbor_sim[key])

        if neighbor_sim[parent] > tau:
            # above threshold--> direct child
            D.add_node(tag)
```

```
            D.add_edge(parent, tag)
        else:
    #         D.add_edge(root, descendant)  # do not enforce single taxonomy
            # New "top-level" tag
            D.add_node(tag)
            pass

        if dynamic:
            # recalculate node centralities after removing each <tag>
            # EXPENSIVE.
            G.remove_node(tag)
            cent = pd.Series(cent_dict[cent_prog](G)).sort_values(ascending=False)
        else:
            cent.drop(tag, inplace=True)

    if verbose:
        print root # most "general" topic
        print nx.isolates(D) # child-less nodes (i.e. central AND dissimilar)


    D.remove_nodes_from(nx.isolates(D))  # not useful for taxonomy

    if dotfile is not None:
        from networkx.drawing.nx_pydot import graphviz_layout, write_dot
        D.graph['graph']={'rankdir':'LR', 'splines':'true',
                          'ranksep':'3'}
        write_dot(D, dotfile)

    return D

D = heymann_taxonomy(dist_mat,
                     cent_prog='pr', # dynamic=True,
                     dotfile='tax.dot')
```

In [35]:

```
# from networkx.drawing.nx_pydot import graphviz_layout, write_dot
# write_dot(D, 'tax.dot')
!dot -Tpng tax.dot >tax.png
```



electrical
cabinet
electrical_cabinet
light
workzone
door
door_interlock
interlock
st_5
st_5_brush_unit
st_5_brush
motor
fan
cooling_fan
st_12
starter
jet
coolant
tank
vogel_tank
coolant_tank
turret
turret_3
b_turret
chip
chip_conveyor
chip_guard
conveyor
clutch
disc
clutch_disc
conveyor_clutch
gear
offload
belt
conveyor_belt
chamfer
offload conveyor
guard
main
coolant_pump
base
pump
pump_motor
coolant_pump_motor
vacuum
oil
oil_line
hydraulic_oil
floor
plug
connector
unit_motor
wire
motor_starter
connection
brake
fuse
bus
breaker
contactor
motor_contactor
bolt
conveyor_motor
rod
inverter_valve
chip_breaker_valve
st_8
st_2
st_2_drill
indexer_valve
solenoid_valve
control
panel
control_panel
bleeder_valve
coil
table_valve
control_valve
wheel_control_valve
solenoid
table
up_down
table_up_down
table_index
load_valve
breaker_valve
wheel
regulating_wheel
grind_wheel
table_index_valve
bleeder
chip_breaker
rack
hydraulic_return
hydraulic_pressure
hydraulic_pump
hydraulic_line
hydraulic_filter
hydraulic_hose
inverter
valve
filter
cnc
hydraulic_fluid
chain
bar_feeder_chain
feeder_chain
bar_loader_chain
loader_chain
link
feed_pressure
pusher
bar_change
end
counter
high_speed_counter
high_speed
bar_clamp
switch
float_switch
limit_switch
pressure_switch
selector
proximity
proximity_sensor
proximity_switch
table_down_proximity
proximity_cable
selector_switch
float
cutoff_unit
stick
saw_unit
pulley
hydraulic
ring
fluid
bar
bar_end
mode
bar_loader
feed
feed_chain
feeder
dog
push_dog
bar_feeder
loader
pressure
air_pressure
gauge
pressure_gauge
accumulator
high_pressure
high_pressure_pump
high_pressure_coolant
low_pressure
bladder
operator
hydraulic_return_line
seal
rings
pack
power_pack
iemca
flag
face_travel_flag
face
face_travel
travel_flag
track
iemca_track
guide
channel
rear
iemca_rear
hose
coolant_hose
line
air
air_line
cylinder
return_line
coolant_line
hydraulic_motor
flange
sensor
cable
sensor_cable
cable_connection
gripper
encoder
part
chute
catcher
part_catcher
collet
housing
filter_housing
flag_sensor
thread
thread_unit
unit
shelf
saw
saw_attachment
blade
attachment
pin
screw
ball_screw
axis_ball
axis_ball_screw
axis
x_axis
z_axis
c_axis
clamp
stock_clamp
stock
tool
tool_detection
holder
laser
tool_holder
tool_clamp
clamp_screw
hsk_clamp
hsk
set_screw
ball
spindle
st_9
st_4
st_3
st_10
st_11
spindle_drive
st_2_spindle
spindle_contactor
main_spindle
sub_spindle
bearing
spindle_bearing
drive
drive_shaft
module
performance_module
shaft
drive_belt
lead_screw
spare
vogel
fitting
lube
vogel_lube
person
machine
brush
brush_unit_stick
brush_unit_motor
brush_unit
head
st_6
drill
cross
cross_drill_head
drill_head
detector
drill_detector
cross_drill
xd
xd_head
saw_head