In [1]:
```
from lda2vec import preprocess, Corpus
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns
%matplotlib inline
sns.set_context('poster')
```

You must be using a very recent version of pyLDAvis to use the lda2vec outputs. As of this writing, anything past Jan 6 2016 or this commit `14e7b5f60d8360e` should work. You can do this quickly by installing it directly from master like so:

In [2]:
```
# pip install -U git+https://github.com/bmabey/pyLDAvis.git@master#egg=pyLDAvis
```

In [2]:
```
import pyLDAvis
pyLDAvis.enable_notebook()
```

Reading in the saved model story topics

After runnning `lda2vec_run.py` script in `examples/hacker_news/lda2vec` directory `topics.story.pyldavis.npz` and `topics.author.pyldavis.np` topic-to-word probabilities and frequencies. What's left is to visualize and label each topic from the it's prevalent words.

In [3]:
```
npz = np.load(open('topics.story.pyldavis.npz', 'r'))
dat = {k: v for (k, v) in npz.iteritems()}
dat['vocab'] = dat['vocab'].tolist()
```

In [4]:
```
top_n = 10
topic_to_topwords = {}
for j, topic_to_word in enumerate(dat['topic_term_dists']):
    top = np.argsort(topic_to_word)[::-1][:top_n]
    msg = 'Topic %i '  % (j+ 1)
    top_words = [dat['vocab'][i].strip()[:35] for i in top]
    msg += ' '.join(top_words)
    print msg
    topic_to_topwords[j] = top_words
```

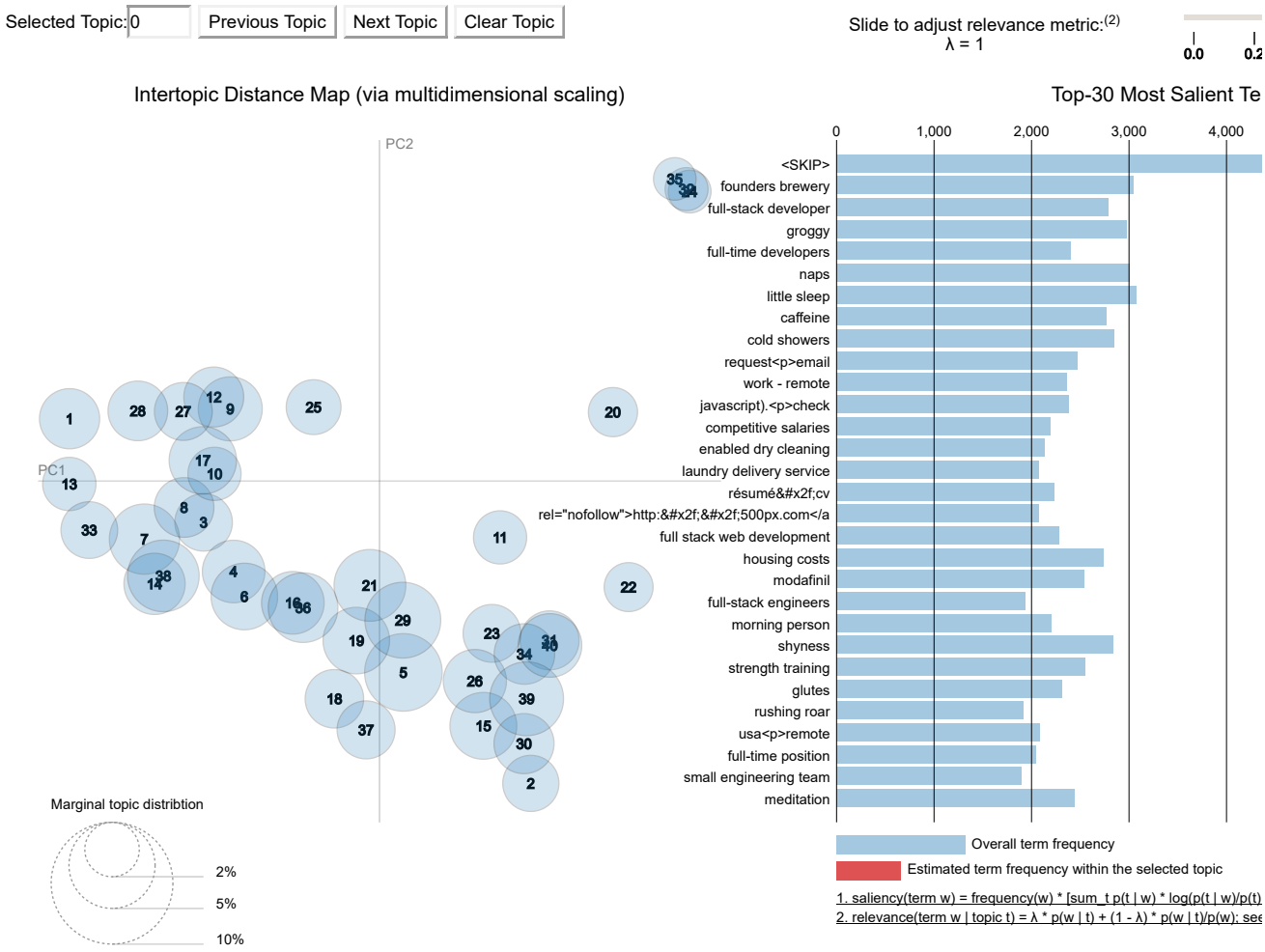
```
Topic 1 rent control gentrification basic income more housing home ownership housing affordable housing gentrifying housing pric
Topic 2 trackpoint xmonad mbp. macports thinkpad mbp sizeup out_of_vocabulary crashplan mechanical keyboard
Topic 3 algebra calculus ebonics adhd reading speed math education meditations new words common core math classes
Topic 4 cree top gear charging stations model s b&#38;n 1gbps mattresses at&#38;t broder starz
Topic 5 google+ bing default search engine ddg g+ igoogle !g g+. google+. google reader
Topic 6 cyclists f-35 tesla&#x27;s hyperloop cyclist electric cars nest protect pedestrians autonomous cars fuel costs
Topic 7 ender dawkins asperger ramanujan atheists savages gladwell isaacson alan turing psychopathy
Topic 8 bitcoins bitcoin btc bitcoin price mtgox bitcoin economy btc. index funds liquidity bitcoin exchanges
Topic 9 college education mba program idea guys business degree college dropouts gpa graduates higher education rock star grad s
Topic 10 morning person melatonin cardio naps adderall sleep schedule caffeine pullups weight training little sleep
Topic 11 first language sicp. sicp ror. object orientation cormen category theory the good parts htdp learn you a
Topic 12 current salary hiring managers hiring manager technical interviews performance reviews 60+ hours interviewing interviev
Topic 13 helmet cardio carbs fasting diet lasik biking soylent vitamin d veggies
Topic 14 horvath ortiz eich eich&#x27;s swartz adria adria richards whistleblower kerr edward snowden
Topic 15 2fa gpg fastmail factor authentication abp lastpass factor auth https encrypt pgp
Topic 16 tau quantum effects neutrinos qm asimov particles galaxies consciousness particle cosine
Topic 17 asian parents grades ap courses gpa grade inflation college experience good grades khan majoring hs
Topic 18 factor authentication fbi icann search warrant tor encrypting passwords privacy rights encrypt us jurisdiction
Topic 19 apple pay apple music whatsapp at&amp;t ad blockers moto g patreon fire phone google play music prime video
Topic 20 slicehost yes<p>willing seeking freelancer - remote request<p>email work - remote remote<p>i yes<p>technologies remote<
Topic 21 chargify padmapper spreedly godaddy merchant account namecheap recurly paypal free users cc details
Topic 22 monotouch wp7 .net. bizspark .net stack .net webos microsoft stack 3.3.1 tizen
Topic 23 <SKIP> nim go&#x27;s raii kotlin callbacks haskell&#x27;s generics nimrod ints
Topic 24 rel="nofollow">http:&#x2f;&#x2f;tur swiftstack relocation great communication skills esoterics small engineering team t
Topic 25 current salary hourly rates equity elance hourly rate odesk freelancing living expenses invoice exploding offer
Topic 26 verdana semicolons rubular textarea whitespace selectors indent .vimrc indentation bookmarklet
Topic 27 holacracy apprenticeships common core phd&#x27;s &quot;cultural fit&quot vc&#x27;s basic income &quot;culture&quot oper
Topic 28 morning person shyness depression little sleep therapist naps work/life balance burnout introverts workaholism
Topic 29 prismatic new page karma high karma magcloud submit button karma system clickpass cornify average karma
Topic 30 start menu xfce kde 11.04 unity gnome 8.1 direct3d dual boot wayland
Topic 31 checked exceptions try/catch list comprehensions <SKIP> callbacks orm dependency injection static typing stm function p
Topic 32 great communication skills top-floor office swiftstack small engineering team backend engineers rel="nofollow">http:&#x
Topic 33 nuclear power thorium fossil fuels nuclear plants uranium gdp nuclear waste economic growth fiat currency climate chang
Topic 34 <SKIP> es6 react&#x27;s ast react components callbacks javascript&#x27;s mixins go&#x27;s browserify
Topic 35 offer:<p><pre><code ca. full swiftstack ca<p>==========<p>aclima backend engineers laundry delivery service team.<p>we
Topic 36 rim elop plurk zynga pincus patent system crunchpad software patents nortel patents htc
Topic 37 apple watch the surface pro 16:9 hdmi mac pro winamp good battery life upgradable big iphone steam box
Topic 38 snowden real terrorists nsa&#x27;s terrorism whistleblower edward snowden assange terrorists 9&#x2f;11 &quot;war
Topic 39 consolas st2 inconsolata .vimrc vim zsh vim bindings iterm2 arrow keys svg
Topic 40 cloudfront docker dockerfile docker container graphql gitlab docker containers coreos dokku gogs
```

Visualize story topics

In [5]:
```
import warnings
warnings.filterwarnings('ignore')
prepared_data_story = pyLDAvis.prepare(dat['topic_term_dists'], dat['doc_topic_dists'],
                                       dat['doc_lengths'] * 1.0, dat['vocab'], dat['term_frequency'] * 1.0, sort_topics=False)
```

In [6]:
```
pyLDAvis.display(prepared_data_story)
```

Out[6]:



I spent an hour looking through the visualization above and manually labeled each topic, which is reproduced below.

In [164]:
```
labels = [   'housing social issues, affordability, rent',
    'computer hardware and monitors',
    'math, language, meditation and education',
    'cars and entertainment',
    'bing, google, facebook, search engines',
    'transportation and military',
    'technology in the media and society',
    'finance and bitcoin',
    'higher education, business and grad schools',
    'sleep, stimulants, and excercise',
    'programming (introductory)',
    'interviews, severance, salaries, reviews',
    'health, dieting and nutrition',
    'civil rights, gay rights, sexual harassment, free speech',
    'internet security, passwords, authentication',
    'physics and computer science',
    'academic success, testing, grades',
    'privacy, FBI, wiretapping',
    'internet media, streaming, advertising, communication',
    'job posting (remote)',
    'online payments, banking, domain registration, user accounts',
    'programming frameworks, stacks, ecosystems, OSs',
    'programming (advanced)',
    'job posting (general)',
    'freelancing, salary, equity',
    'design, typography, user experience',
    'tech culture, stem workers, bootcamps',
    'mental health, introversion, therapy, work/life balance',
    'karma, votes, comments, stories, rss',
    'desktop environments, linux, xp, gnome',
    'programming (theory)',
    'job posting (general)',
    'energy, public policy',
    'programming (browser)',
    'job posting (general)',
    'software patents, patent trolls, patent law',
    'games, gaming hardware and displays',
    'terrorism, surveillance, consitutionality, ',
    'code editors, programming fonts, terminals',
    'cloud technology, docker, AWS'
]
labels = np.array(labels)
```

Article Features

In [7]:
```
features = pd.read_csv('../data/hacker_news_comments.csv', encoding='utf8')
```

In [8]:
```
# Convert all integer arrays to int32
for col, dtype in zip(features.columns, features.dtypes):
    if dtype is np.dtype('int64'):
        features[col] = features[col].astype('int32')
```

In [9]:
```
max_length = 250   # Limit of 250 words per comment
min_author_comments = 50  # Exclude authors with fewer comments
nrows = None  # Number of rows of file to read; None reads in full file
```

In [10]:
```
# Extract numpy arrays over the fields we want covered by topics
# Convert to categorical variables
author_counts = features['comment_author'].value_counts()
to_remove = author_counts[author_counts < min_author_comments].index
mask = features['comment_author'].isin(to_remove).values
author_name = features['comment_author'].values.copy()
author_name[mask] = 'infrequent_author'
features['comment_author'] = author_name
authors = pd.Categorical(features['comment_author'])
author_id = authors.codes
author_name = authors.categories
story_id = pd.Categorical(features['story_id']).codes
# Chop timestamps into days
story_time = pd.to_datetime(features['story_time'], unit='s')
days_since = (story_time - story_time.min()) / pd.Timedelta('1 day')
time_id = days_since.astype('int32')
days_since = (story_time - story_time.min()) / pd.Timedelta('1 day')
features['story_id_codes'] = story_id
features['author_id_codes'] = story_id
features['time_id_codes'] = time_id
features['days_since'] = days_since
features['story_dt'] = story_time
```

In [12]:
```
features.tail()
```

Out[12]:

	story_id	story_time	story_url	story_text	story_author	comment_id	comment_text	comment_author	comm
1165434	1013531	1261638606	NaN	For the year 2010, I plan to:\n1. Learn Clojur...	aitoehigie	1013543	I plan to end 2010 with 10x as many customers ...	cperciva	
1165435	1013531	1261638606	NaN	For the year 2010, I plan to:\n1. Learn Clojur...	aitoehigie	1013710	Being very close to graduate in the end of the...	infrequent_author	
1165436	4312761	1343662100	http://code.google.com/p/chromium/issues/detai...	NaN	eranation	4313810	Not surprising. The amount of aggressive...	infrequent_author	
1165437	9804349	1435663051	http://blogs.aws.amazon.com/security/post/TxCK...	NaN	ukj	9804795	If I counted right: <p><pre><code> OCaml TLS: ...	edwintorok	
1165438	6765099	1384901786	http://www.theatlantic.com/technology/archive/...	NaN	sinak	6767538	We are educated to speak well our language (en...	infrequent_author	

In [13]:
```
features.to_pickle("../data/features.pd")
```

Individual documents

In [353]:
```
top_urls = features['story_url'].value_counts().index
mask = features['story_url'] == top_urls[1]
story_id_code = features[mask].story_id_codes.values[0]
story_id_url = features[mask].story_url.values[0]
```

In [354]:
```
story_id_url
```

Out[354]:
```
u'http://googleblog.blogspot.com/2013/03/a-second-spring-of-cleaning.html'
```

In [355]:
```
topics=dat['doc_topic_dists'][story_id_code]
```

In [356]:
```
msg = "{fraction:02d}% {text:s}"
for idx in np.argsort(topics)[::-1][:5]:
    print msg.format(fraction=int(100.0 * topics[idx]), text=labels[idx])
```

```
27% bing, google, facebook, search engines
15% karma, votes, comments, stories, rss
08% online payments, banking, domain registration, user accounts
07% internet security, passwords, authentication
05% computer hardware and monitors
```

Looking at these topics and then reading the HN article comments (u'http://googleblog.blogspot.com/2013/03/a-second-spring-of-cleaning.html') this is about G appropriate that the top topic is about Google itself and the second topic is about RSS.

Plots of topics vs time

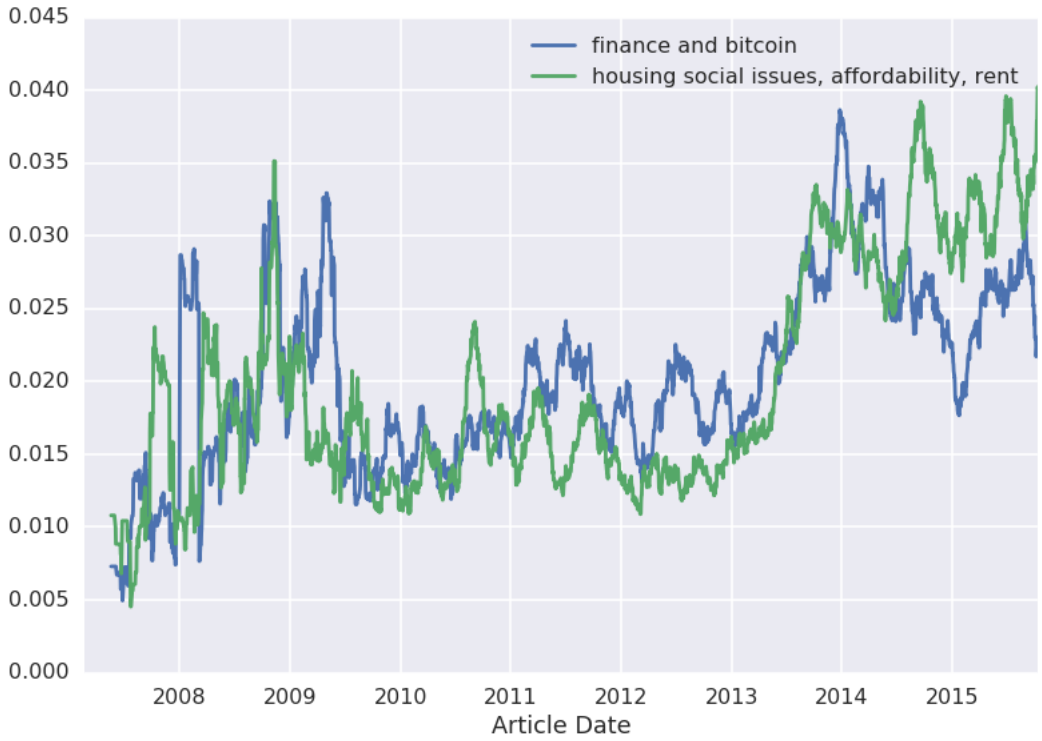
In [359]:
```
cols = [u'story_comment_count', 'story_time', 'story_url', 'story_text', 'days_since', 'story_dt']
stories = features.groupby('story_id_codes')[cols].min().reset_index()
```

In [524]:
```
stories = stories.rename(columns={'story_dt': 'Article Date'})
```

In [527]:
```
story_topics = pd.DataFrame(dict(story_id_codes=np.arange(dat['doc_topic_dists'].shape[0])))
for idx in range(len(labels)):
    story_topics[labels[idx]] = dat['doc_topic_dists'][:, idx]
trends = stories.merge(story_topics, on='story_id_codes')
trends['day'] = np.floor(trends['days_since'].values)
by_day = pd.pivot_table(trends, index=['day', 'story_time'])
```

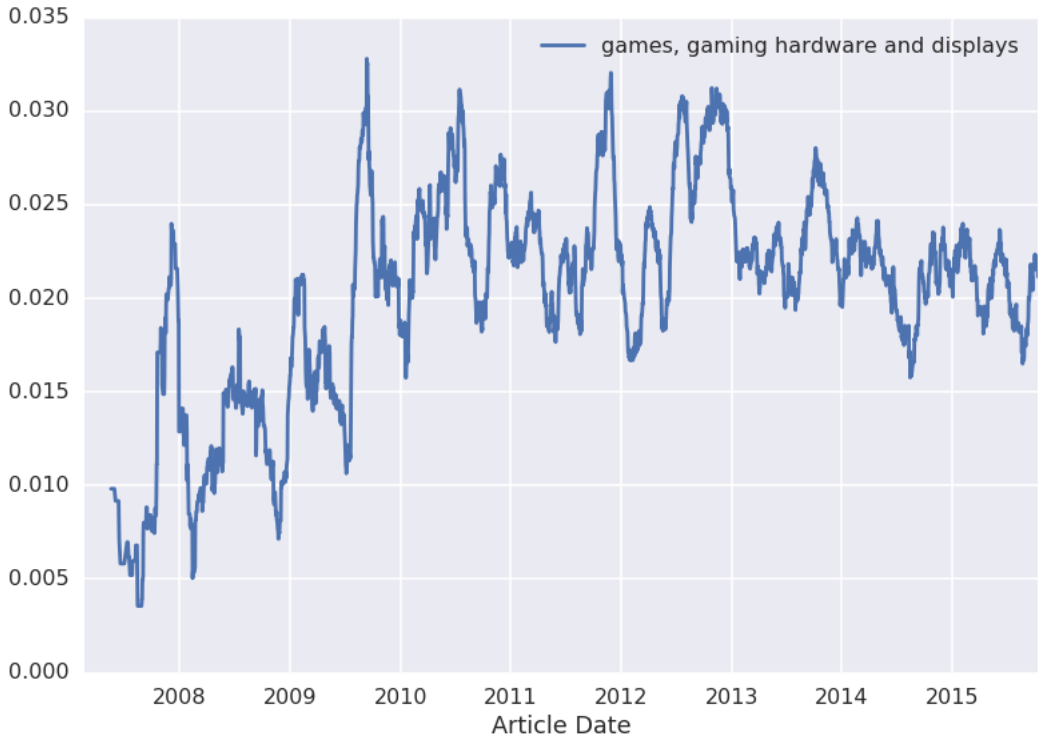
In [528]:
```
mass = lambda x: ((x) * 1.0).sum() / x.shape[0]
window = 56.0
aggs = {'finance and bitcoin': mass,
        'housing social issues, affordability, rent': mass}
pd.rolling_mean(trends.groupby(trends['Article Date'].dt.date).agg(aggs), window).plot()
```

Out[528]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8c65d15550>
```



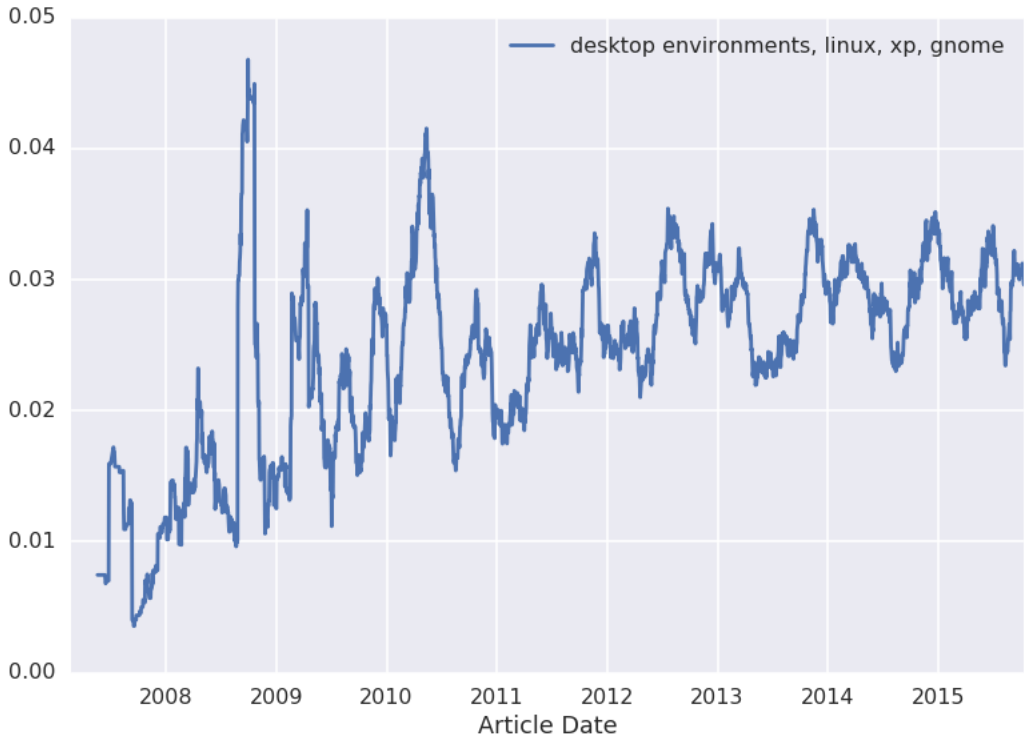
In [529]:
```
aggs = {'games, gaming hardware and displays': mass}
pd.rolling_mean(trends.groupby(trends['Article Date'].dt.date).agg(aggs), window).plot()
```

Out[529]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8c65d15090>
```



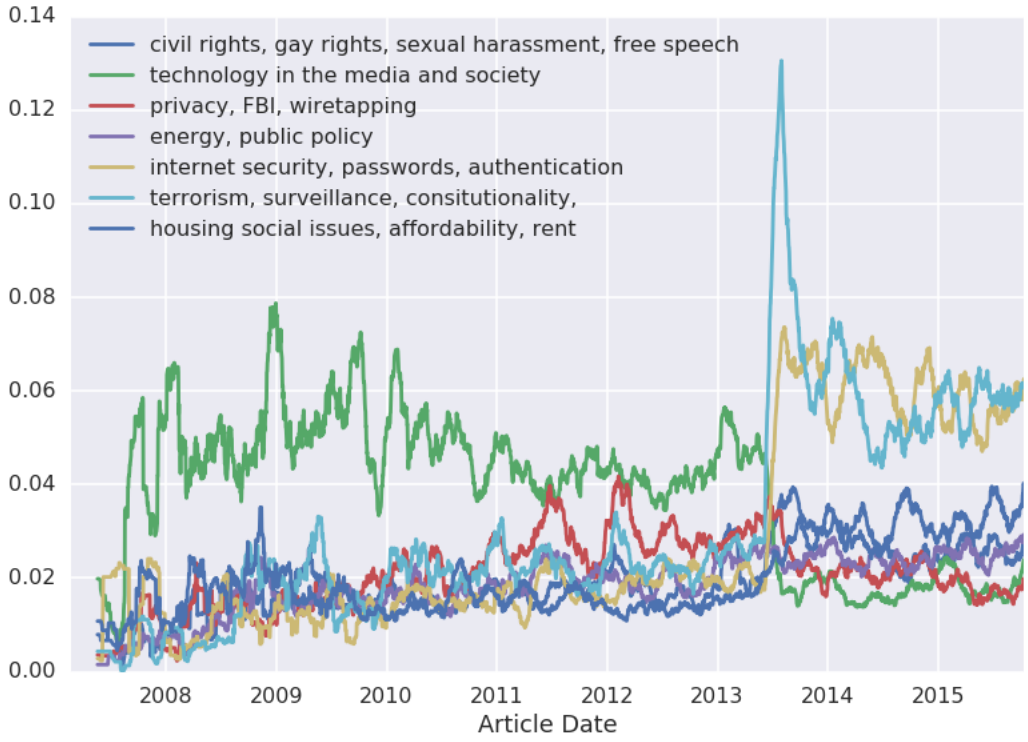
In [530]:
```
aggs = {'desktop environments, linux, xp, gnome': mass}
pd.rolling_mean(trends.groupby(trends['Article Date'].dt.date).agg(aggs), window).plot()
```

Out[530]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8c65713750>
```



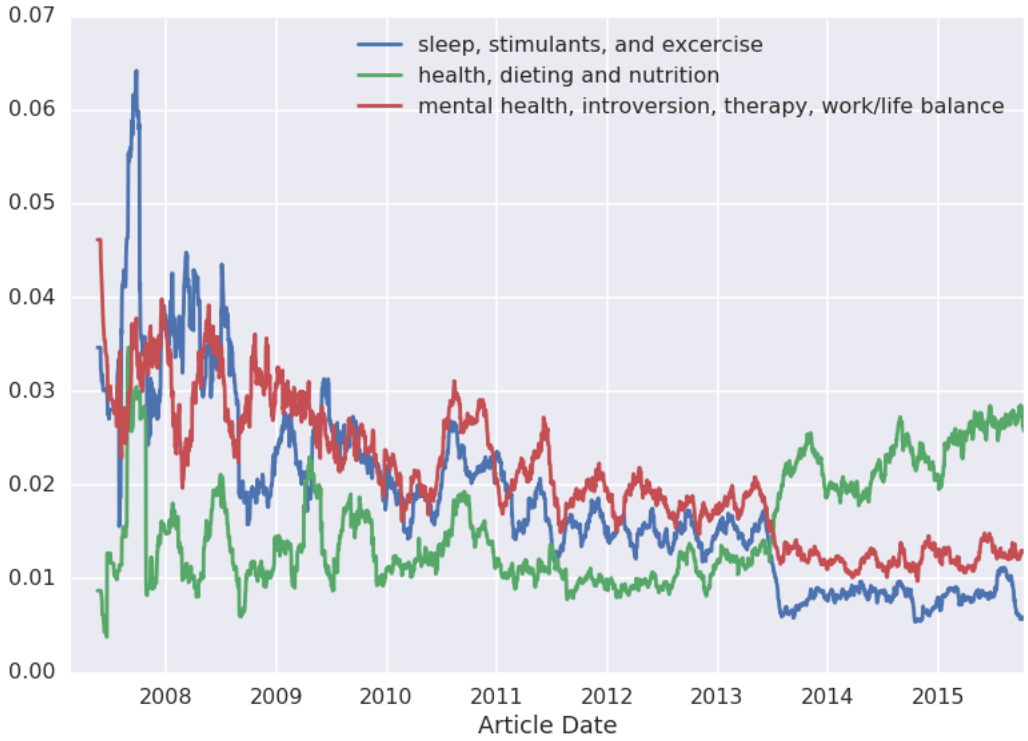
In [531]:
```
aggs = {
    'housing social issues, affordability, rent': mass,
    'technology in the media and society': mass,
    'civil rights, gay rights, sexual harassment, free speech':mass,
    'internet security, passwords, authentication': mass,
    'privacy, FBI, wiretapping':mass,
    'energy, public policy':mass,
    'terrorism, surveillance, consitutionality, ':mass,
    }
pd.rolling_mean(trends.groupby(trends['Article Date'].dt.date).agg(aggs), window).plot()
```

Out[531]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8c580aa450>
```



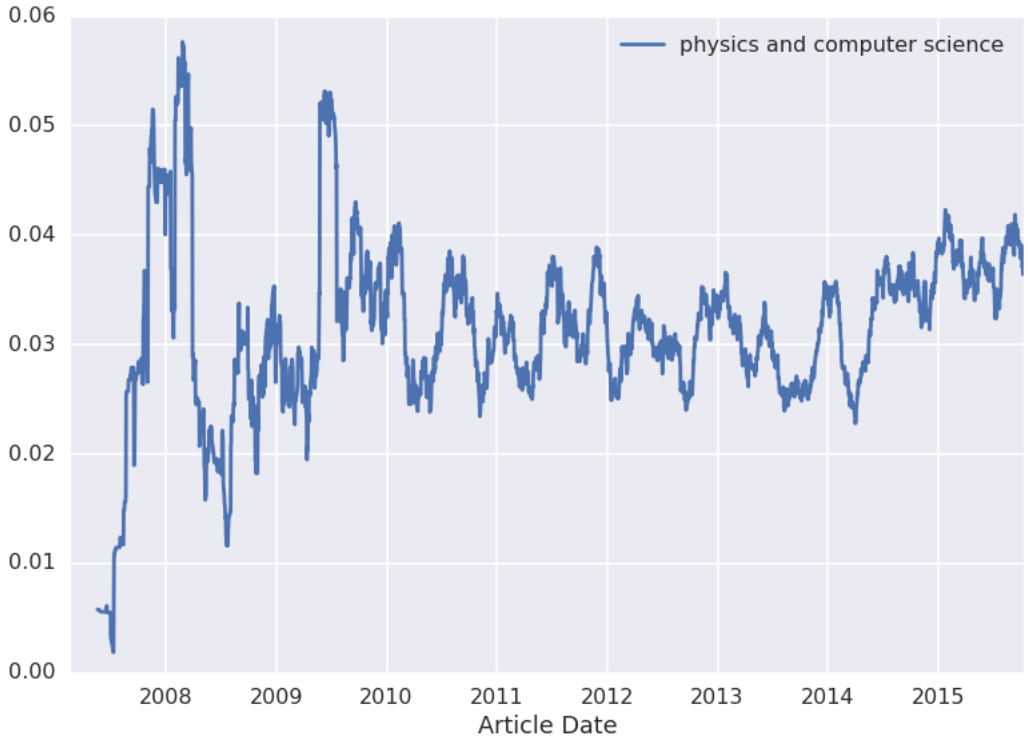
In [532]:
```
aggs = {
    'health, dieting and nutrition': mass,
    'sleep, stimulants, and excercise':mass,
    'mental health, introversion, therapy, work/life balance':mass}
pd.rolling_mean(trends.groupby(trends['Article Date'].dt.date).agg(aggs), window).plot()
```

Out[532]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8c6560ae90>
```



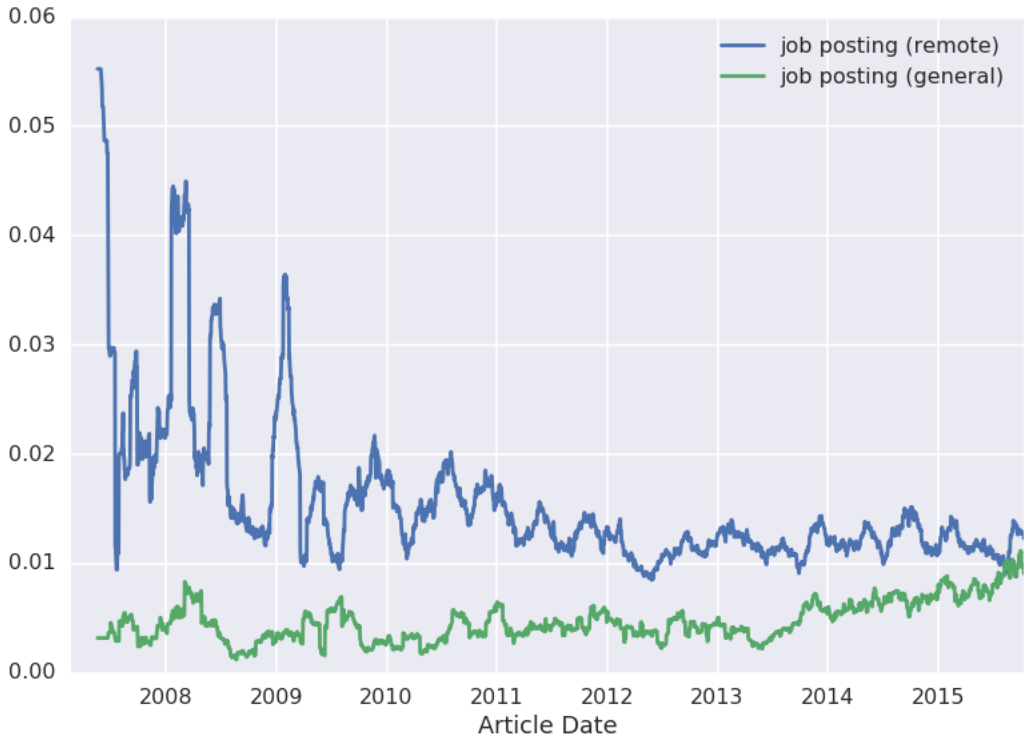
In [533]:
```
aggs = {
    'physics and computer science': mass,    }
pd.rolling_mean(trends.groupby(trends['Article Date'].dt.date).agg(aggs), window).plot()
```

Out[533]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8c66840150>
```



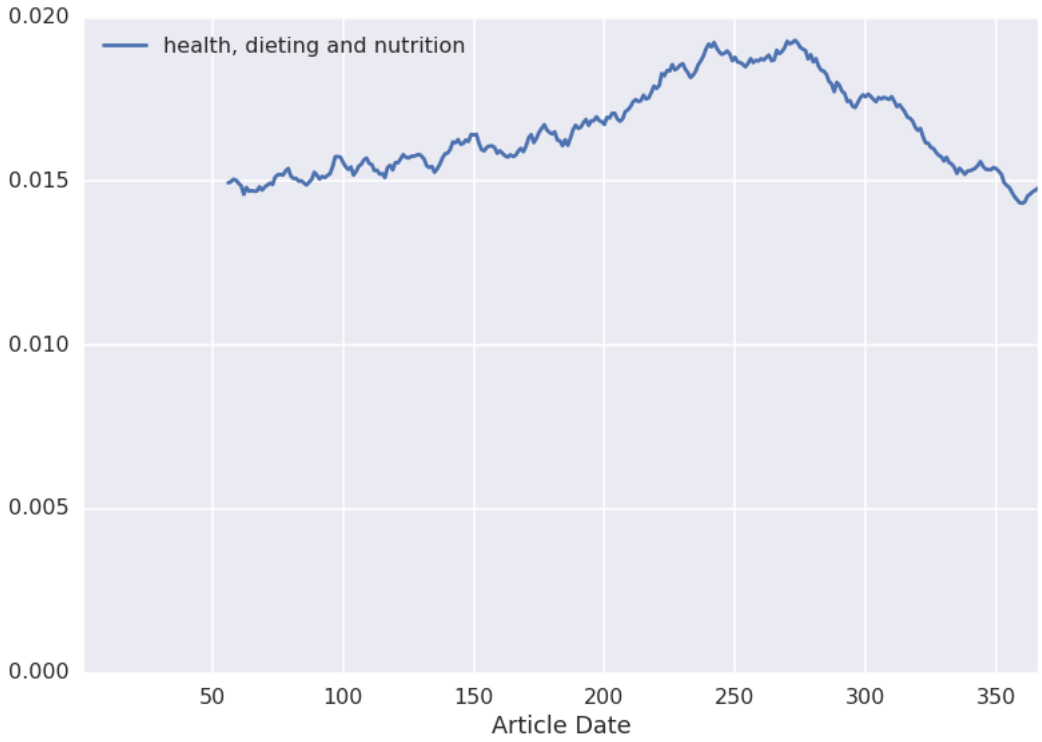
In [534]:
```
aggs = {'job posting (remote)': mass, 'job posting (general)': mass}
pd.rolling_mean(trends.groupby(trends['Article Date'].dt.date).agg(aggs), window).plot()
```

Out[534]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8c670f2e90>
```



In [536]:
```
aggs = {'health, dieting and nutrition': mass}
pd.rolling_mean(trends.groupby(trends['Article Date'].dt.dayofyear).agg(aggs), 56.0).plot(ylim=[0, 0.02])
```

Out[536]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8c66451390>
```



Visualize Author Topics

Unfortunately, this is a failed experiment! Looking at the user-level topics just generates nonsense. There might be one or two coherent topics in the bunch, but little sense.

In [ ]:
```
prepared_data_author = pyLDAvis.prepare(dat['topic_term_dists'], dat['doc_topic_dists'],
                                        dat['doc_lengths'] * 1.0, dat['vocab'], dat['term_frequency'] * 1.0)
```

In [7]:

```
npz = np.load(open('topics.author.pyldavis.npz', 'r'))
dat = {k: v for (k, v) in npz.iteritems()}
dat['vocab'] = dat['vocab'].tolist()
top_n = 10
topic_to_topwords = {}
for j, topic_to_word in enumerate(dat['topic_term_dists']):
    top = np.argsort(topic_to_word)[::-1][:top_n]
    msg = 'Topic %i '  % j
    top_words = [dat['vocab'][i].strip()[:35] for i in top]
    msg += ' '.join(top_words)
    print msg
    topic_to_topwords[j] = top_words
```

```
Topic 0 out_of_vocabulary submitted article <SKIP> cognate work-sample test href="http://norvig.com/experiment xtopdf learners c
Topic 1 out_of_vocabulary  <SKIP> wasen&#x27;t  probally twiddla --and huge engagement &quot;rent
Topic 2  out_of_vocabulary <SKIP> alot ie- ve wasen&#x27;t realy nt bad product
Topic 3 portfolio:<p extensive experience building e-com heta resourceful.<p>reach tax experts music artists here&#x27;re href="
Topic 4 rel="nofollow">http:&#x2f;&#x2f;tur accountants.<p courses.<p tax experts intuit]<p rel="nofollow">http:&#x2f;&#x2f;git
Topic 5 submitted article great web software substantial annual turnover july 2007 limited-time online sales current name-brand
Topic 6 out_of_vocabulary i>don't twiddla padova   -- i>very</i i>nothing</i i>can't</i
Topic 7 fun office environment substantial annual turnover general hacking skills 21st century.<p>we&#x27;ve great web software
Topic 8 nt pinchzoom .. nuuton beeing newscred atleast fun office environment theres
Topic 9 pinchzoom ^_^ .. nt  smth uhm fun office environment out_of_vocabulary heta
Topic 10 welcome<p>scribd fun office environment small businesses&#x2f;individuals top 100 website lifestyle categories availabl
Topic 11 fun office environment welcome<p>scribd talented hackers general hacking skills top 100 website karts mobile or web dev
Topic 12 out_of_vocabulary <SKIP> alot  don&#x27;t b&#x2f;c wasen&#x27;t &quot;rent better state toffeescript
Topic 13 out_of_vocabulary p><pre><code <SKIP>   /code></pre </a><p><pre><code < > --------------------------
Topic 14  twiddla out_of_vocabulary <SKIP> 've n't 'd 'm i padova
Topic 15 <SKIP> out_of_vocabulary  supplant complexity patent protection magnitude real cost efficiently increasingly
Topic 16 out_of_vocabulary  <SKIP>  p><pre><code  --------------------------  </a><p><pre><code
Topic 17 tricky integration test limited-time online sales homeware great web software current name-brand goods lifestyle catego
Topic 18 out_of_vocabulary submitted article portfolio:<p extensive experience building e-com href="http://norvig.com/experiment
Topic 19  out_of_vocabulary <SKIP> ie-  401k twiddla &quot;rent er nurse /
```

In [9]:
```
pyLDAvis.display(prepared_data_author)
```

Out[9]: