In [1]:
```
import datetime
import dateutil
import gzip
import numpy
import matplotlib.pyplot as plt
import random
import scipy
import sklearn
import tensorflow as tf
import time
from collections import defaultdict
from fastFM import als
from sklearn import linear_model
```

Data is available at http://cseweb.ucsd.edu/~jmcauley/pml/data/. Download and save to your own directory

In [2]:
```
dataDir = "/home/jmcauley/pml_data/"
```

Autoregression

Example based on Bay-Area bike-share data. Extract the time information from the events.

In [3]:
```
events = {}

for f in [dataDir + "201408_trip_data.csv", dataDir + "201402_trip_data.csv"]:
    f = open(f, 'r')
    l = f.readline()
    for l in f:
        l = l.split(',')
        tripID = l[0]
        timeString = l[2]
        timeUnix =\
            time.mktime(datetime.datetime.strptime(timeString, "%m/%d/%Y %H:%M"))
        events[tripID] = [timeUnix, timeString]
```

Find the earliest event (so that we can sort events from the first to the last hour)

In [4]:
```
earliest = None
for event in events:
    if earliest == None or events[event][0] < earliest[0]:
        earliest = events[event]
```

In [5]:
```
earliestTime = earliest[0]
```

Count events by hour

In [6]:
```
hourly = defaultdict(int)

for event in events:
```

```
    t = events[event][0]
    hour = int(t - earliestTime) // (60*60)
    hourly[hour] += 1
```

Autoregressive feature representation. Here we don't include a bias term, though could easily include one.

In [7]:
```
def feature(hour):
    previousHours = []
    # Features for last 5 hours, one day ago, one week ago, and one year ago
    for i in [1,2,3,4,5,24,24*7,24*7*365]:
        previousHour = hour - i
        previousHourExists = previousHour in hourly
        if previousHourExists:
            previousHours += [hourly[previousHour]]
        else:
            previousHours += [0]
    return previousHours
```

In [8]:
```
X = [feature(x) for x in hourly]
y = [hourly[x] for x in hourly]
```

In [9]:
```
model = sklearn.linear_model.LinearRegression(fit_intercept=False)
model.fit(X, y)
theta = model.coef_
```

The observation one week ago is the most predictive, followed by the observation from the previous hour:

In [10]:
```
theta
```

Out[10]:
```
array([ 0.47105067, -0.28432565,  0.10555845,  0.01445134, -0.02131945,
        0.17501989,  0.53969635,  0.        ])
```

Sliding window

Parse ratings and timestamps from (a small fraction of) Goodreads fantasy novel data

In [11]:
```
ratingsTime = []
z = gzip.open(dataDir + "goodreads_reviews_fantasy_paranormal.json.gz")

for l in z:
    d = eval(l)
    t = dateutil.parser.parse(d['date_updated'])
    ratingsTime.append((t,d['rating']))
    if len(ratingsTime) >= 50000:
        break
```

Sort observations by time

In [12]:
```
ratingsTime.sort()
```

```
len(ratingsTime)
```

Out[12]:

```
50000
```

Keep track of a window (wSize) of ratings and timestamps (the raw time is just for printing the plot)

In [13]:

```
wSize = 1000
x = [r[0] for r in ratingsTime] # as raw times
y = [r[1] for r in ratingsTime] # ratings
xu = [time.mktime(d.timetuple()) for d in x] # as unix times
```

Use a dynamic-programming approach to build the sliding window

In [14]:

```
xSum = sum(xu[:wSize])
ySum = sum(y[:wSize])
sliding = []
```

In [15]:

```
for i in range(wSize,len(x)-1):
    xSum += xu[i] - xu[i-wSize]
    ySum += y[i] - y[i-wSize]
    sliding.append((xSum*1.0/wSize,ySum*1.0/wSize))
```

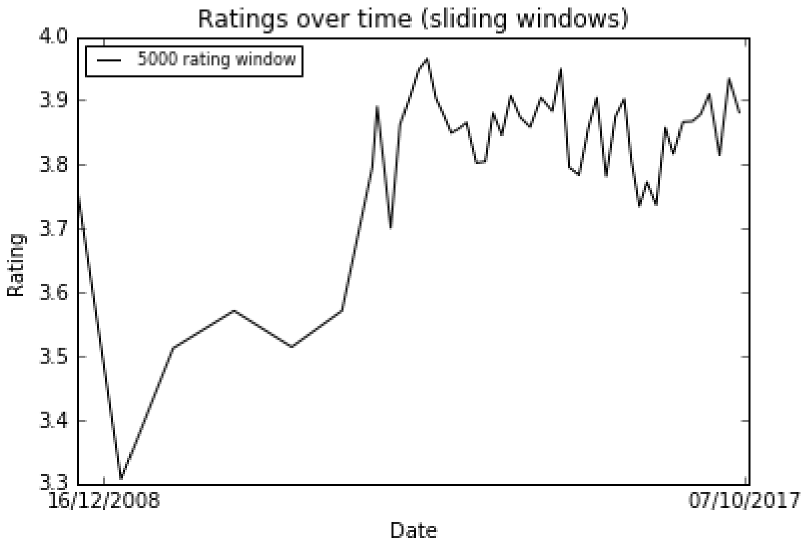
X and Y coordinates for plotting

In [16]:

```
X = [a[0] for a in sliding]
Y = [a[1] for a in sliding]
```

In [17]:

```
plt.plot(X[::1000],Y[::1000], label="5000 rating window", color='k')
plt.xticks([X[600], X[-350]], [x[wSize+600].strftime("%d/%m/%Y"), x[-350].strfti
plt.xlim(X[0], X[-1])
plt.ylabel("Rating")
plt.xlabel("Date")
plt.legend(loc="best",fontsize=8)
plt.title("Ratings over time (sliding windows)")
plt.show()
```



FPMC in Tensorflow

In [18]:

```
def parse(path):
    g = gzip.open(path, 'r')
    for l in g:
        yield eval(l)
```

Extract the interaction data, including the timestamps associated with each interaction

In [19]:

```
userIDs = {}
itemIDs = {}
interactions = []
interactionsPerUser = defaultdict(list)

for d in parse(dataDir + "goodreads_reviews_comics_graphic.json.gz"):
    u = d['user_id']
    i = d['book_id']
    t = d['date_added']
    r = d['rating']
    dt = dateutil.parser.parse(t)
    t = int(dt.timestamp())
    if not u in userIDs: userIDs[u] = len(userIDs)
    if not i in itemIDs: itemIDs[i] = len(itemIDs)
    interactions.append((t,u,i,r))
    interactionsPerUser[u].append((t,i,r))
```

Interaction with timestamp

In [20]:

```
interactions[0]
```

Out[20]:

```
(1386269065, 'dc3763cdb9b2cae805882878eebb6a32', '18471619', 3)
```

In [21]:

```
len(interactions)
```

Out[21]:

```
542338
```

Sort interactions by time (including interaction sequences for each user). Useful when building data structures that include adjacent pairs of interactions (but consider whether this is desirable if making train/test splits!).

In [22]:
```
interactions.sort()
```

In [23]:
```
itemIDs['dummy'] = len(itemIDs)
```

Build a data structure including users, items, and their previous items

In [24]:
```
interactionsWithPrevious = []

for u in interactionsPerUser:
    interactionsPerUser[u].sort()
    lastItem = 'dummy'
    for (t,i,r) in interactionsPerUser[u]:
        interactionsWithPrevious.append((t,u,i,lastItem,r))
        lastItem = i
```

In [25]:
```
itemsPerUser = defaultdict(set)
for _,u,i,_ in interactions:
    itemsPerUser[u].add(i)
```

In [26]:
```
items = list(itemIDs.keys())
```

Define the tensorflow model. Similar to models from Chapter 5, with the addition of the term associated with the previous interaction.

In [27]:
```
optimizer = tf.keras.optimizers.Adam(0.1)
```

FMPC class. UI and IJ are given as initialization options, allowing us to exclude certain terms (for exercises later).

In [28]:
```
class FPMC(tf.keras.Model):
    def __init__(self, K, lamb, UI = 1, IJ = 1):
        super(FPMC, self).__init__()
        # Initialize variables
        self.betaI = tf.Variable(tf.random.normal([len(itemIDs)],stddev=0.001))
        self.gammaUI = tf.Variable(tf.random.normal([len(userIDs),K],stddev=0.00
        self.gammaIU = tf.Variable(tf.random.normal([len(itemIDs),K],stddev=0.00
        self.gammaIJ = tf.Variable(tf.random.normal([len(itemIDs),K],stddev=0.00
        self.gammaJI = tf.Variable(tf.random.normal([len(itemIDs),K],stddev=0.00
        # Regularization coefficient
        self.lamb = lamb
        # Which terms to include
        self.UI = UI
        self.IJ = IJ

    # Prediction for a single instance
    def predict(self, u, i, j):
```

```
        p = self.betaI[i] + self.UI * tf.tensordot(self.gammaUI[u], self.gammaIU
                            self.IJ * tf.tensordot(self.gammaIJ[i], self.gammaJI
        return p

    # Regularizer
    def reg(self):
        return self.lamb * (tf.nn.l2_loss(self.betaI) +\
                            tf.nn.l2_loss(self.gammaUI) +\
                            tf.nn.l2_loss(self.gammaIU) +\
                            tf.nn.l2_loss(self.gammaIJ) +\
                            tf.nn.l2_loss(self.gammaJI))

    def call(self, sampleU, # user
                   sampleI, # item
                   sampleJ, # previous item
                   sampleK): # negative item
        u = tf.convert_to_tensor(sampleU, dtype=tf.int32)
        i = tf.convert_to_tensor(sampleI, dtype=tf.int32)
        j = tf.convert_to_tensor(sampleJ, dtype=tf.int32)
        k = tf.convert_to_tensor(sampleK, dtype=tf.int32)
        gamma_ui = tf.nn.embedding_lookup(self.gammaUI, u)
        gamma_iu = tf.nn.embedding_lookup(self.gammaIU, i)
        gamma_ij = tf.nn.embedding_lookup(self.gammaIJ, i)
        gamma_ji = tf.nn.embedding_lookup(self.gammaJI, j)
        beta_i = tf.nn.embedding_lookup(self.betaI, i)
        x_uij = beta_i + self.UI * tf.reduce_sum(tf.multiply(gamma_ui, gamma_iu)
                       self.IJ * tf.reduce_sum(tf.multiply(gamma_ij, gamma_ji)
        gamma_uk = tf.nn.embedding_lookup(self.gammaUI, u)
        gamma_ku = tf.nn.embedding_lookup(self.gammaIU, k)
        gamma_kj = tf.nn.embedding_lookup(self.gammaIJ, k)
        gamma_jk = tf.nn.embedding_lookup(self.gammaJI, j)
        beta_k = tf.nn.embedding_lookup(self.betaI, k)
        x_ukj = beta_k + self.UI * tf.reduce_sum(tf.multiply(gamma_uk, gamma_ku)
                       self.IJ * tf.reduce_sum(tf.multiply(gamma_kj, gamma_jk)
        return -tf.reduce_mean(tf.math.log(tf.math.sigmoid(x_uij - x_ukj)))
```

In [29]:

```
modelFPMC = FPMC(5, 0.00001)
```

In [30]:

```
def trainingStep(model, interactions):
    with tf.GradientTape() as tape:
        sampleU, sampleI, sampleJ, sampleK = [], [], [], []
        for _ in range(100000):
            _,u,i,j,_ = random.choice(interactions) # positive sample
            k = random.choice(items) # negative sample
            while k in itemsPerUser[u]:
                k = random.choice(items)
            sampleU.append(userIDs[u])
            sampleI.append(itemIDs[i])
            sampleJ.append(itemIDs[j])
            sampleK.append(itemIDs[k])

        loss = model(sampleU,sampleI,sampleJ,sampleK)
        loss += model.reg()
    gradients = tape.gradient(loss, model.trainable_variables)
    optimizer.apply_gradients((grad, var) for
                              (grad, var) in zip(gradients, model.trainable_vari
```

```
                                              if grad is not None)
    return loss.numpy()
```

Run 100 batches

In [31]:
```
for i in range(100):
    obj = trainingStep(modelFPMC, interactionsWithPrevious)
    if (i % 10 == 9): print("iteration " + str(i+1) + ", objective = " + str(obj
```

```
iteration 10, objective = 0.48359895
iteration 20, objective = 0.45931146
iteration 30, objective = 0.45187306
iteration 40, objective = 0.45339736
iteration 50, objective = 0.4563751
iteration 60, objective = 0.45513394
iteration 70, objective = 0.4522531
iteration 80, objective = 0.45192516
iteration 90, objective = 0.45243126
iteration 100, objective = 0.4488452
```

In [ ]:
```

```

Exercises

7.1

(still using the hourly bikeshare interaction data from examples above)

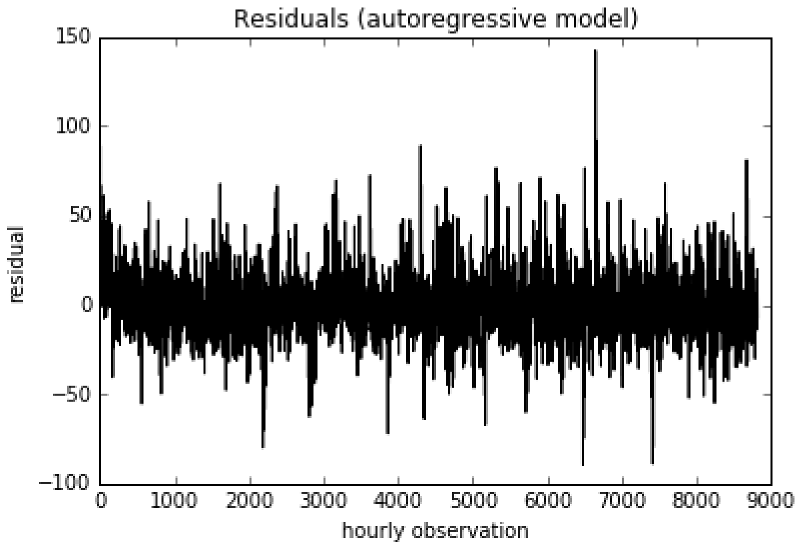
In [32]:
```
xsort = list(hourly.keys())
xsort.sort()
X = [feature(x) for x in xsort]
y = [hourly[x] for x in xsort]
```

In [33]:
```
model = sklearn.linear_model.LinearRegression(fit_intercept=False)
model.fit(X, y)
theta = model.coef_
```

In [34]:
```
ypred = model.predict(X)
```

In [35]:
```
res = y - ypred
```

In [36]:
```
plt.plot(xsort, res, color='k')
plt.ylabel("residual")
plt.xlabel("hourly observation")
plt.title("Residuals (autoregressive model)")
plt.show()
```



7.2

(using Goodreads data from examples above)

In [37]:
```
len(interactions)
```

Out[37]:
```
542338
```

In [38]:
```
interactionsTrain = interactionsWithPrevious[:500000]
interactionsTest = interactionsWithPrevious[500000:]
```

The FPMC implementation we built above allowed us to control which terms (user/item or item/item) were included

In [39]:
```
modelFPMC = FPMC(5, 0.001, 1, 1)
modelMF = FPMC(5, 0.001, 1, 0)
modelFMC = FPMC(5, 0.001, 0, 1)
```

In [40]:
```
interactionsTestPerUser = defaultdict(set)
itemSet = set()
for _,u,i,j,_ in interactionsTest:
    interactionsTestPerUser[u].add((i,j))
    itemSet.add(i)
    itemSet.add(j)
```

In [41]:
```
def AUCu(model, u, N):
    win = 0
    if N > len(interactionsTestPerUser[u]):
        N = len(interactionsTestPerUser[u])
    positive = random.sample(interactionsTestPerUser[u],N)
    negative = random.sample(itemSet,N)
    for (i,j),k in zip(positive,negative):
        sp = model.predict(userIDs[u], itemIDs[i], itemIDs[j]).numpy()
        sn = model.predict(userIDs[u], itemIDs[k], itemIDs[j]).numpy()
        if sp > sn:
```

```
            win += 1
    return win/N
```

In [42]:

```
def AUC(model):
    av = []
    for u in interactionsTestPerUser:
        av.append(AUCu(model, u, 10))
    return sum(av) / len(av)
```

In [43]:

```
for model,name in [(modelFPMC,"FPMC"), (modelMF,"MF"), (modelFMC,"FMC")]:
    for i in range(100):
        obj = trainingStep(model, interactionsTrain)
        if (i % 10 == 9): print("iteration " + str(i+1) + ", objective = " + str
    print(name + " AUC = " + str(AUC(model)))
```

```
iteration 10, objective = 1.1740164
iteration 20, objective = 0.9275751
iteration 30, objective = 0.74895376
iteration 40, objective = 0.7000136
iteration 50, objective = 0.6867862
iteration 60, objective = 0.68066156
iteration 70, objective = 0.67874753
iteration 80, objective = 0.67833763
iteration 90, objective = 0.67842907
iteration 100, objective = 0.6778376
FPMC AUC = 0.7603135912093875
iteration 10, objective = 1.2148852
iteration 20, objective = 0.926385
iteration 30, objective = 0.87147164
iteration 40, objective = 0.7567261
iteration 50, objective = 0.6929133
iteration 60, objective = 0.68015
iteration 70, objective = 0.67653024
iteration 80, objective = 0.67463166
iteration 90, objective = 0.6742325
iteration 100, objective = 0.6739234
MF AUC = 0.749866757590709
iteration 10, objective = 1.2447531
iteration 20, objective = 1.1213548
iteration 30, objective = 1.0458206
iteration 40, objective = 0.76125264
iteration 50, objective = 0.7084387
iteration 60, objective = 0.69079274
iteration 70, objective = 0.68107307
iteration 80, objective = 0.67796034
iteration 90, objective = 0.67755425
iteration 100, objective = 0.6774621
FMC AUC = 0.7502356931668346
```

7.3

FISM implementaion, using a factorization machine

In [44]:

```
nItems = len(itemIDs)
nUsers = len(userIDs)
```

In [45]:
```
fismInter = random.sample(interactions,100000)
```

Factorization machine design matrix. Note that we have two sets of features (the user history, and the target item). Both are of dimension nItems.

In [46]:
```
X = scipy.sparse.lil_matrix((len(fismInter), 2*nItems))
```

In [47]:
```
for n in range(len(fismInter)):
    _,u,i,r = fismInter[n]
    item = itemIDs[i]
    history = itemsPerUser[u]
    for j in history:
        if i == j: continue # Exclude the target item from the history
        X[n,itemIDs[j]] = 1.0 / (len(history) - 1) # One-hot encoding, normalize
    X[n,nItems + item] = 1
```

In [48]:
```
y = numpy.array([r for _,_,_,r in fismInter])
```

Fairly slow and memory-hungry (every row contains a copy of a user's history). Could possibly be implemented faster in Tensorflow.

In [49]:
```
fm = als.FMRegression(n_iter=1000, init_stdev=0.1, rank=5, l2_reg_w=0.1, l2_reg_
```

In [50]:
```
X_train,y_train = X[:90000],y[:90000]
X_test,y_test = X[90000:],y[90000:]
```

In [51]:
```
fm.fit(X_train, y_train)
```

Out[51]:
```
FMRegression(init_stdev=0.1, l2_reg=0, l2_reg_V=0.5, l2_reg_w=0.1, n_iter=1000,
             random_state=123, rank=5)
```

In [52]:
```
y_pred = fm.predict(X_test)
```

In [53]:
```
def MSE(predictions, labels):
    differences = [(x-y)**2 for x,y in zip(predictions,labels)]
    return sum(differences) / len(differences)
```

In [54]:
```
MSE(y_pred, y_test)
```

Out[54]:
```
1.6111794992027808
```

7.4

(still using Goodreads data)

In [55]:
```
interactions.sort()
```

In [56]:
```
interactionsPerItem = defaultdict(list)
for t,u,i,r in interactions:
    interactionsPerItem[i].append((t,u,r))
```

In [57]:
```
random.shuffle(interactions)
```

Regression-based approach. Just collect past K interactions (ratings) as features.

In [58]:
```
def feat(t,u,i):
    older = [r for (q,u,r) in interactionsPerItem[i] if q < t] # Collect previou
    f = []
    for k in range(1,6):
        try:
            f += [0,older[-k]] # Previous rating
        except Exception as e:
            f += [1,0] # Or missing value indicator if we don't have history of
    if len(older):
        f += [0,sum(older)/len(older)] # Add feature for the average (going beyo
    else:
        f += [1,0] # Missing value indicator if no interaction history
    return f + [1]
```

In [59]:
```
X = [feat(t,u,i) for t,u,i,_ in interactions]
y = [r for _,_,_,r in interactions]
```

In [60]:
```
X_train, X_test = X[:400000],X[400000:]
y_train, Y_test = y[:400000],y[400000:]
```

In [61]:
```
model = sklearn.linear_model.LinearRegression(fit_intercept=False)
model.fit(X_train, y_train)
theta = model.coef_
theta
```

Out[61]:
```
array([-1.65119630e+10,  2.30226517e-02,  1.77267075e-01,  4.43439484e-02,
        1.67497635e-01,  4.66625690e-02,  1.63910866e-01,  4.96263504e-02,
        1.32824421e-01,  4.92523909e-02,  1.65119630e+10,  2.88013697e-01,
        1.90127087e+00])
```

In [62]:
```
y_pred = model.predict(X_test)
```

In [63]:
```
MSE(y_pred, y_test)
```

Out[63]:
```
1.3810078092245268
```

Factorization machine-based approach. Copy the same features from the model above, but also include a user term. In theory, this should allow us to learn how sensitive a particular user is to herding.

In [64]:
```
XF = scipy.sparse.lil_matrix((len(interactions), nUsers + len(X[0])))
```

In [65]:
```
for n in range(len(interactions)):
    _,u,i,r = interactions[n]
    user = userIDs[u]
    XF[n,user] = 1
    for j in range(len(X[n])): # Copy features from previous model
        XF[n,nUsers+j] = X[n][j]
```

In [66]:
```
fm = als.FMRegression(n_iter=1000, init_stdev=0.1, rank=5, l2_reg_w=0.1, l2_reg_
```

In [67]:
```
y = numpy.array(y)
```

In [68]:
```
X_train,y_train = XF[:400000],y[:400000]
X_test,y_test = XF[400000:],y[400000:]
```

In [69]:
```
fm.fit(X_train, y_train)
```

Out[69]:
```
FMRegression(init_stdev=0.1, l2_reg=0, l2_reg_V=0.5, l2_reg_w=0.1, n_iter=1000,
             random_state=123, rank=5)
```

In [70]:
```
y_pred = fm.predict(X_test)
```

In [71]:
```
MSE(y_pred, y_test)
```

Out[71]:
```
1.5863953730808005
```

In [ ]: