Please install arviz for the visualization of bayesian model

In [19]:
```
%matplotlib inline
import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
import seaborn as sns
import scipy.stats as stats
import pymc3 as pm
import sys


# import a new plot module to plot all graphs of PyMC3.
import arviz
import warnings
warnings.simplefilter('ignore', UserWarning)
```

In [20]:
```
google=pd.read_csv("google.csv",index_col=0)
google.head()
```

Out[20]:

Date	Open	High	Low	Close	Adj Close	Volume
2014-12-31	529.795471	531.141724	524.360352	524.958740	524.958740	1368200
2015-01-02	527.561584	529.815369	522.665039	523.373108	523.373108	1447500
2015-01-05	521.827332	522.894409	511.655243	512.463013	512.463013	2059800
2015-01-06	513.589966	514.761719	499.678131	500.585632	500.585632	2899900
2015-01-07	505.611847	505.855164	498.281952	499.727997	499.727997	2065000

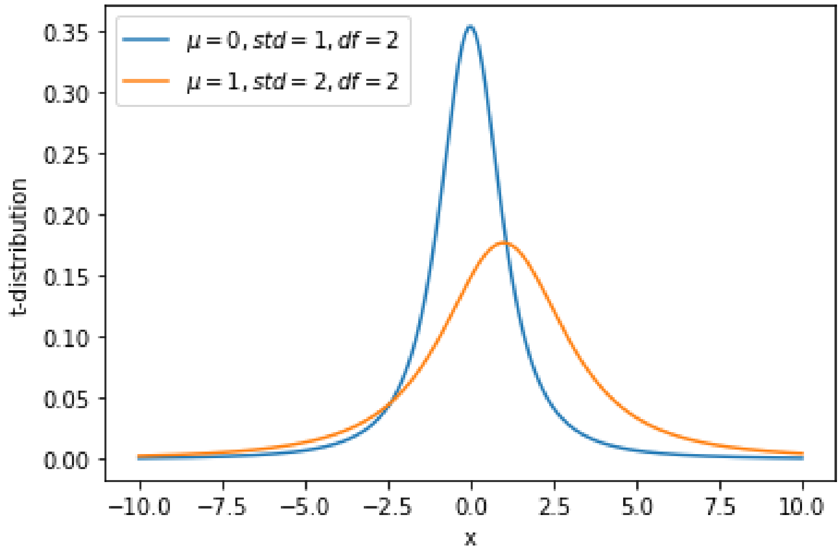
In [21]:
```
google.shape
```

Out[21]: (1447, 6)

Bayesian Model of Risk and Reward

In [22]:
```
from scipy.stats import t
x = np.linspace(-10,10,200)
plt.plot(x, t.pdf(x,df=2),label='$\mu=0,std=1,df=$'+str(2))

plt.plot(x, t.pdf(x,2,loc=1, scale=2),label='$\mu=1,std=2,df=$'+str(2)
plt.legend(loc='upper left')
plt.xlabel("x")
plt.ylabel("t-distribution")
```

Out[22]: Text(0, 0.5, 't-distribution')

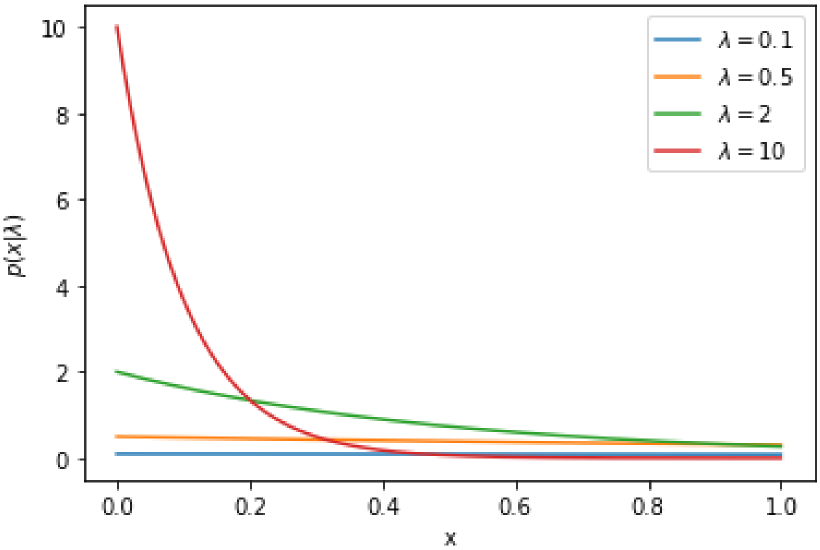


In [23]:
```
from scipy.stats import expon
```

In [24]:
```
ld=2# lamabda=2
x = np.linspace(0,1,200) # the range is x>=0, we only visualize x in
```

In [25]:
```
for ld in [0.1,0.5,2,10]:
    plt.plot(x,  expon.pdf(x,scale=1/ld),label='$\lambda=$'+str(ld))
    plt.legend()
plt.xlabel("x")
plt.ylabel("$p(x|\lambda)$")
```

Out[25]: Text(0, 0.5, '$p(x|\\lambda)$')



In [26]:
```
google["return"]=google["Close"].pct_change()
google=google.dropna(axis=0)# drop row if the row has NaN
```

In [27]:
```
rmean =google["return"].mean()
rstd=google["return"].std()
```

```
rmean,rstd# realized mean and std from historical data
```

Out[27]: (0.0008546799145806177, 0.016939579481752374)

In [11]:

```
rmean =google["return"].mean()
rstd=google["return"].std()
uniformL = rstd/ 1000 # low bound and upperbound for the uniform prior
uniformU = rstd * 1000

with pm.Model() as sr_model:
    #three prior
    mean = pm.Normal('mean', mu=rmean, sd=rstd)
    std = pm.Uniform('std', lower=uniformL, upper=uniformU)
    df = pm.Exponential('df', 1 / 29,testval=5) + 2.# make the df is a
    # testval is the initial value to start sample.
    # likelihood
    returns = pm.StudentT('returns', nu=df, mu=mean, sd=std, observed=

    sharpe = returns.distribution.mean / returns.distribution.variance
    pm.Deterministic('sharpe', sharpe) # Not a distribution
```

In [12]:

```
tune = 4000
draws = 1000
with sr_model:
    trace = pm.sample(tune=tune,
                      draws=draws,
                      chains=4,random_seed=8888)
```

```
Auto-assigning NUTS sampler...
Initializing NUTS using jitter+adapt_diag...
Multiprocess sampling (4 chains in 2 jobs)
NUTS: [df, std, mean]
```

100.00% [20000/20000 01:03<00:00 Sampling 4 chains, 0 divergences]

```
Sampling 4 chains for 4_000 tune and 1_000 draw iterations (16_000 + 4
_000 draws total) took 99 seconds.
```

In [13]:

```
trace_df = pm.trace_to_dataframe(trace).assign(chain=lambda x: x.index
trace_df.shape
```

Out[13]: (4000, 5)

In [14]:

```
trace_df.head()
```

Out[14]:

	mean	std	df	sharpe	chain
0	0.001156	0.009553	0.462719	0.832620	0
1	0.001271	0.009976	0.893997	1.124110	0
2	0.001160	0.010196	0.879283	0.997885	0
3	0.001025	0.010077	0.582156	0.767040	0

	mean	std	df	sharpe	chain
4	0.001466	0.009939	0.710966	1.198805	0

In [15]:

```
from pymc3.plots import  plot_posterior,traceplot
```

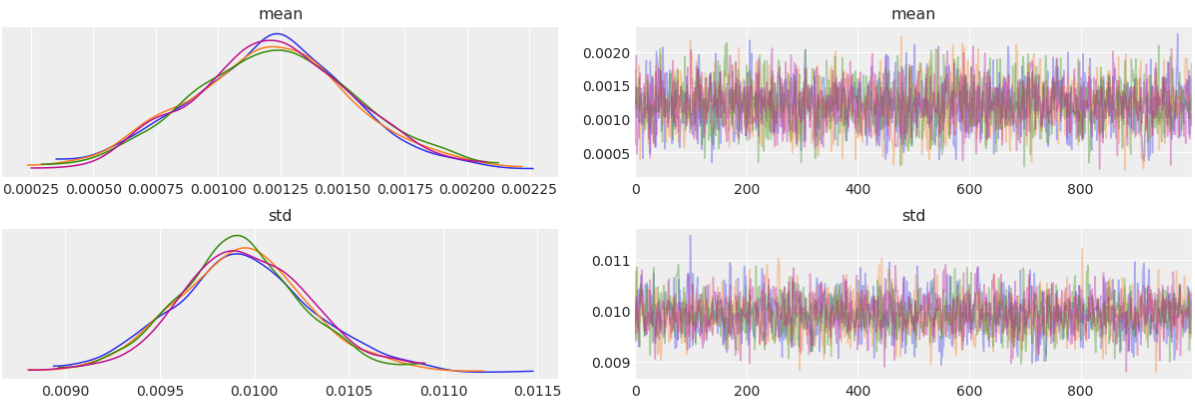
In [16]:

```
import arviz as az

az.style.use("arviz-darkgrid")
az.plot_trace(trace, var_names=("mean", "std"))
```

```
/Users/kenneth/anaconda3/lib/python3.7/site-packages/arviz/data/io_pym
c3.py:91: FutureWarning: Using `from_pymc3` without the model will be
deprecated in a future release. Not using the model will return less a
ccurate and less useful results. Make sure you use the model argument
or call from_pymc3 within a model context.
  FutureWarning,
```

Out[16]:

```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x13cc08898>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x13cbb0e10
>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x13cc6afd0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x13ccafdd8
>]],
      dtype=object)
```



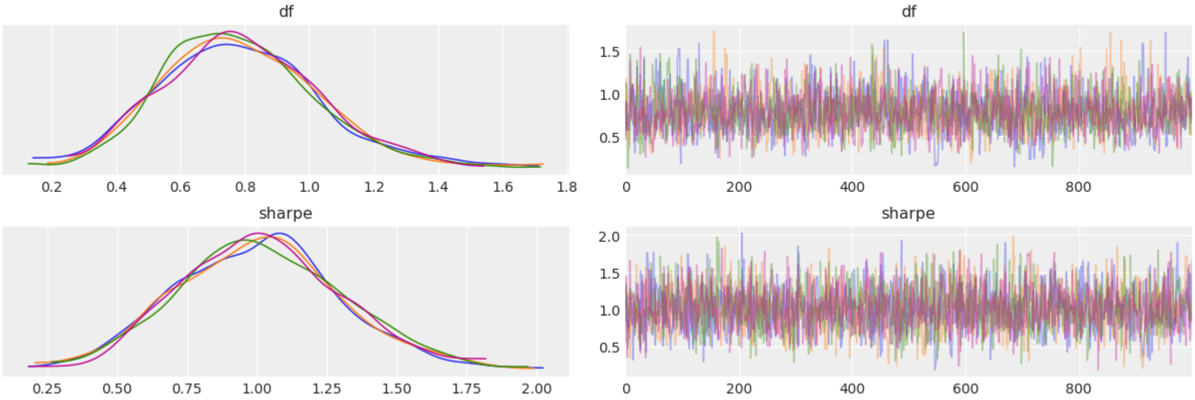
In [17]:

```
az.style.use("arviz-darkgrid")
az.plot_trace(trace, var_names=("df", "sharpe"))
```

```
/Users/kenneth/anaconda3/lib/python3.7/site-packages/arviz/data/io_pym
c3.py:91: FutureWarning: Using `from_pymc3` without the model will be
deprecated in a future release. Not using the model will return less a
ccurate and less useful results. Make sure you use the model argument
or call from_pymc3 within a model context.
  FutureWarning,
```

Out[17]:

```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x13c84ec18>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x1383bf828
>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x136b66eb8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x1360ca390
>]],
      dtype=object)
```

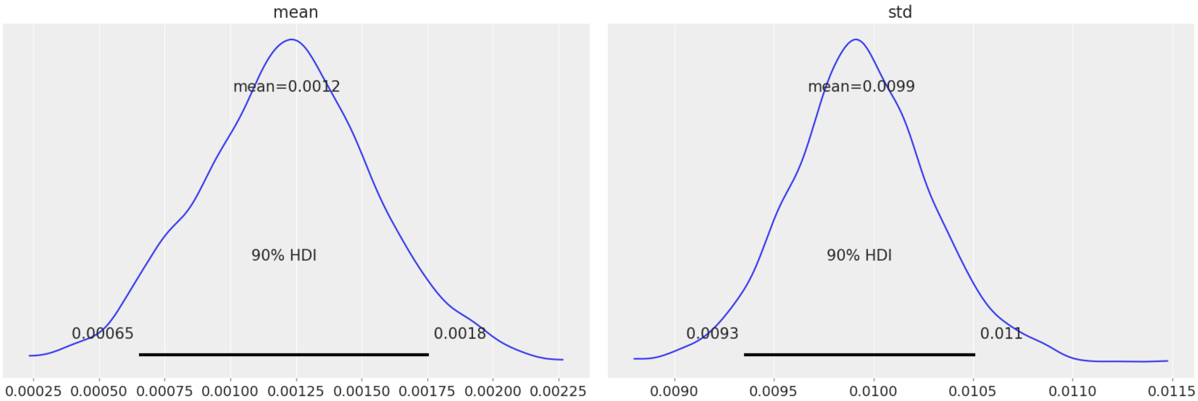


In [ ]:

In [18]:

```
az.style.use("arviz-darkgrid")
ax=az.plot_posterior(trace,var_names=("mean","std"), credible_interval
```

```
/Users/kenneth/anaconda3/lib/python3.7/site-packages/arviz/data/io_pym
c3.py:91: FutureWarning: Using `from_pymc3` without the model will be
deprecated in a future release. Not using the model will return less a
ccurate and less useful results. Make sure you use the model argument
or call from_pymc3 within a model context.
  FutureWarning,
```

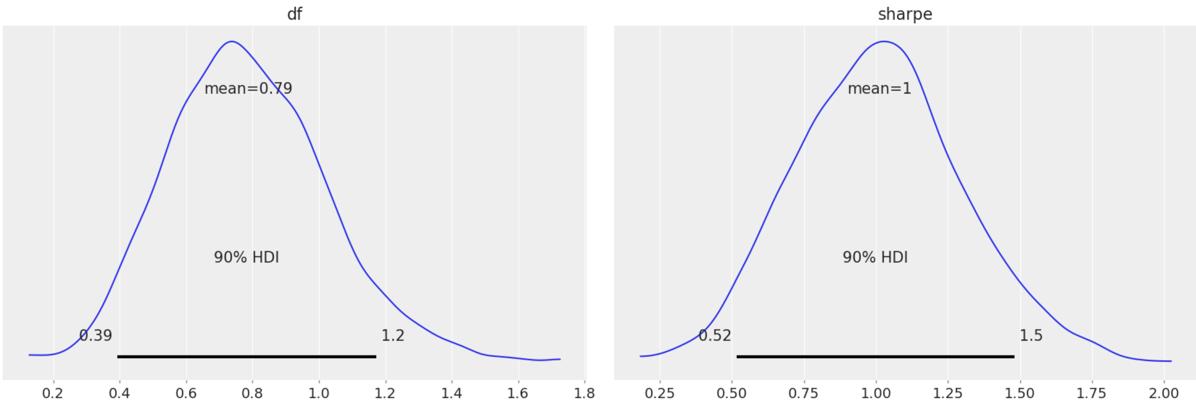


In [19]:

```
az.style.use("arviz-darkgrid")
az.plot_posterior(trace,var_names=("df","sharpe"),credible_interval=0.
```

Out[19]:

```
array([<matplotlib.axes._subplots.AxesSubplot object at 0x1380f1278>,
       <matplotlib.axes._subplots.AxesSubplot object at 0x1382be2e8>],
      dtype=object)
```



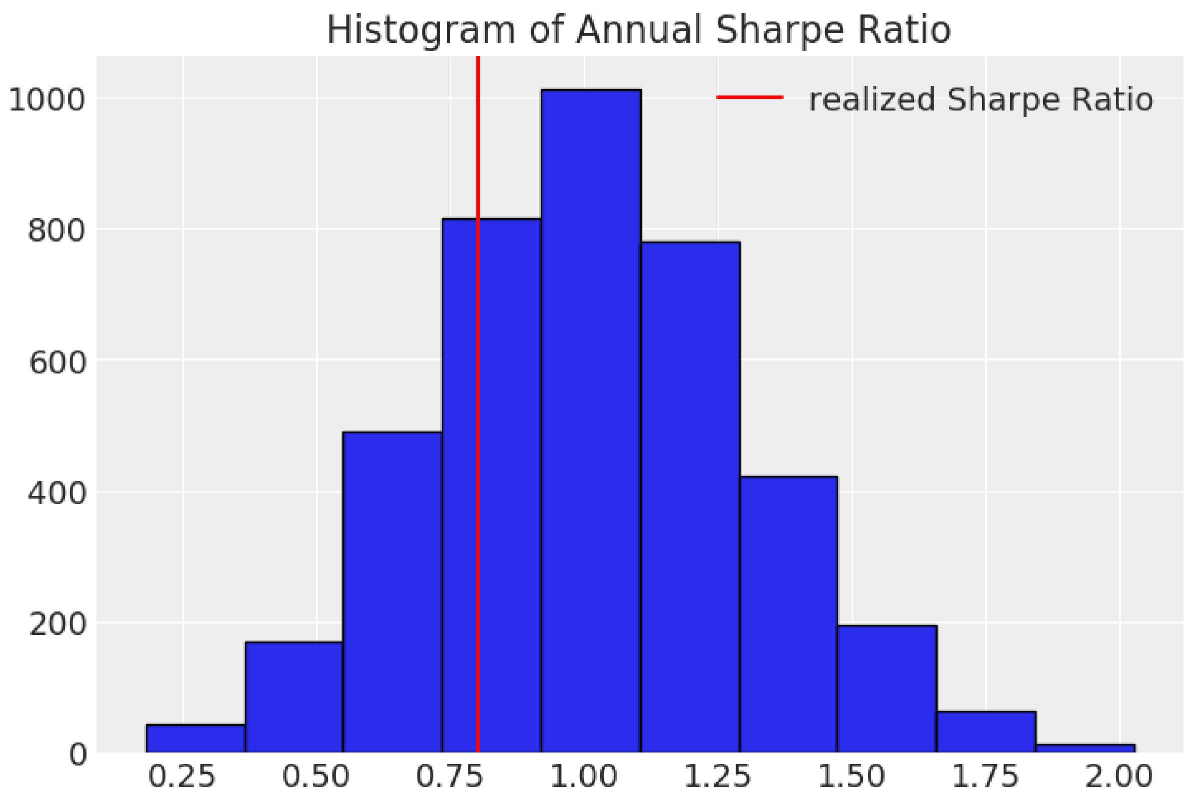
In [20]:

```
plt.hist(trace["sharpe"],ec='black'); # four chains
plt.title("Histogram of Annual Sharpe Ratio")
plt.axvline((252**0.5)*rmean/rstd, color="red", label="realized Sharpe
print((252**0.5)*rmean/rstd)
plt.legend()
```

```
0.800942139199426
```

Out[20]:

```
<matplotlib.legend.Legend at 0x136ae8358>
```



Bayesian Regression with Artifical Data

In [21]:

```
size = 200
beta0 = 1
beta1 = 2
data=pd.DataFrame()
data["x"]=np.linspace(0, 1, size)
data["mu"]=beta0 + beta1 * data["x"]
data["y"]=data["mu"]+np.random.normal(scale=.5, size=size)
```

In [22]:

```
data.head()
```

Out[22]:

	x	mu	y
0	0.000000	1.000000	0.586866
1	0.005025	1.010050	1.074366
2	0.010050	1.020101	1.318150
3	0.015075	1.030151	1.226623
4	0.020101	1.040201	1.498033

Method 1:

In [23]:
```
with pm.Model() as linear_regression1: # model specification
    # Define priors, unique name for each variable
    std = pm.HalfCauchy('sigma', beta=10, testval=1)
    beta0 = pm.Normal('intercept', 0, sd=20)
    beta1 = pm.Normal('slope', 0, sd=20)
    # Define likelihood
    likelihood = pm.Normal('y',
                           mu=beta0 + beta1 *data["x"],
                           sd=std,
                           observed=data["y"])
```

In [24]:
```
tune=6000
draws=2500
with linear_regression1:
    trace1 = pm.sample(tune=tune,
                       draws=draws,
                         cores=1)
```

```
Auto-assigning NUTS sampler...
Initializing NUTS using jitter+adapt_diag...
Sequential sampling (2 chains in 1 job)
NUTS: [slope, intercept, sigma]
```

100.00% [8500/8500 00:37<00:00

Sampling chain 0, 0 divergences]

100.00% [8500/8500 00:25<00:00

Sampling chain 1, 0 divergences]

```
Sampling 2 chains for 6_000 tune and 2_500 draw iterations (12_000 + 5
_000 draws total) took 62 seconds.
The acceptance probability does not match the target. It is 0.88715126
08249326, but should be close to 0.8. Try to increase the number of tu
ning steps.
```

In [25]:
```
trace_df1 = pm.trace_to_dataframe(trace1).assign(chain=lambda x: x.inc
trace_df1.shape
```

Out[25]: (5000, 4)

In [26]:
```
trace_df1.head()
```

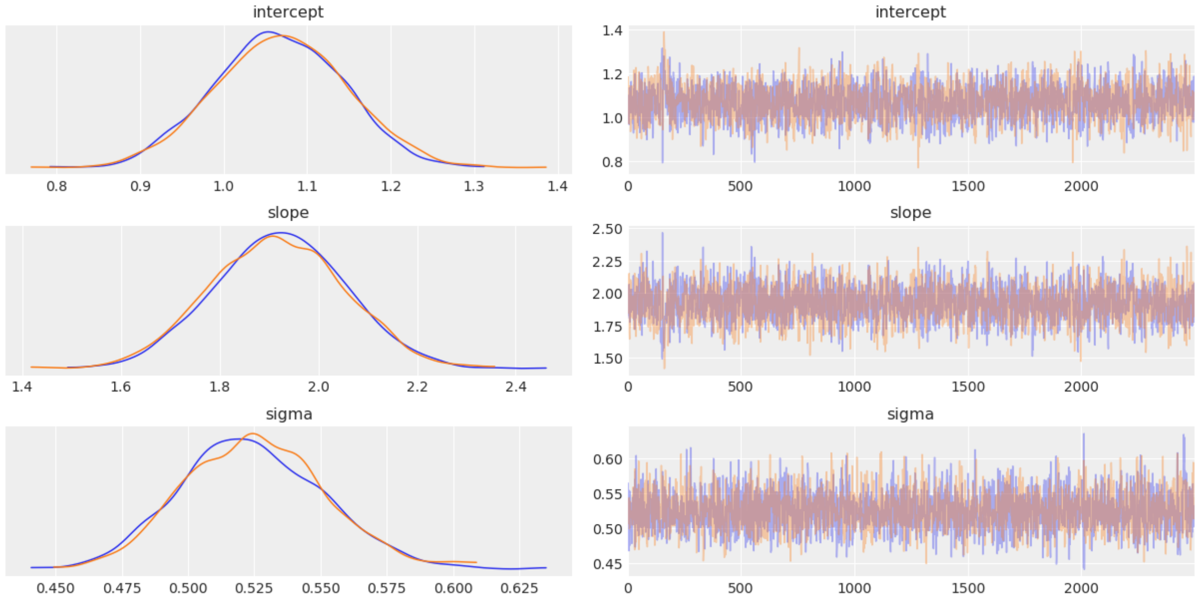
Out[26]:

	intercept	slope	sigma	chain
0	1.099552	1.825028	0.507582	0
1	1.002662	1.991671	0.564299	0
2	1.018408	2.020673	0.497769	0
3	1.018408	2.020673	0.497769	0
4	1.037982	1.994670	0.554240	0

In [27]:
```
az.plot_trace(trace1, var_names=("intercept", "slope","sigma"))
```

```
/Users/kenneth/anaconda3/lib/python3.7/site-packages/arviz/data/io_pym
c3.py:91: FutureWarning: Using `from_pymc3` without the model will be
deprecated in a future release. Not using the model will return less a
ccurate and less useful results. Make sure you use the model argument
or call from_pymc3 within a model context.
  FutureWarning,
```

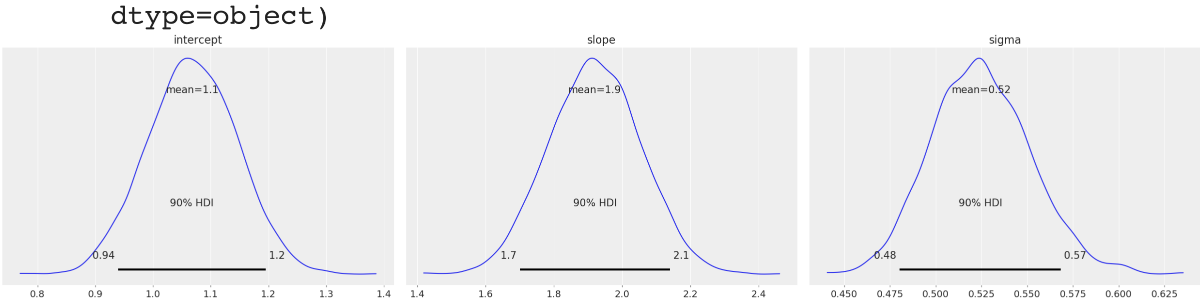
Out[27]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x1375d7860>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x137658240
>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x13c98ee10>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x13cb302b0
>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x137a367f0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x13c81b4a8
>]],
      dtype=object)
```



In [28]:
```
pm.plot_posterior(trace1,credible_interval=0.9)
```

```
/Users/kenneth/anaconda3/lib/python3.7/site-packages/arviz/data/io_pym
c3.py:91: FutureWarning: Using `from_pymc3` without the model will be
deprecated in a future release. Not using the model will return less a
ccurate and less useful results. Make sure you use the model argument
or call from_pymc3 within a model context.
  FutureWarning,
```

Out[28]:
```
array([<matplotlib.axes._subplots.AxesSubplot object at 0x11bbb52b0>,
       <matplotlib.axes._subplots.AxesSubplot object at 0x13c8fd128>,
       <matplotlib.axes._subplots.AxesSubplot object at 0x1383bbf28>],
      dtype=object)
```



In [29]:
```
trace_df1 = pm.trace_to_dataframe(trace1).assign(chain=lambda x: x.inc
trace_df1.shape
```

Out[29]: (5000, 4)

Method II: Use glm()

In [30]:
```
data.head()
```

Out[30]:

	x	mu	y
0	0.000000	1.000000	0.586866
1	0.005025	1.010050	1.074366
2	0.010050	1.020101	1.318150
3	0.015075	1.030151	1.226623
4	0.020101	1.040201	1.498033

In [31]:
```
with pm.Model() as linear_regression2:
    # specify glm and pass in data. The resulting linear model, its li
    # and all its parameters are automatically added to our model.
    pm.glm.GLM.from_formula('y ~ x', data)
```

In [32]:
```
tune=600
draws=2500
with linear_regression2:
    trace2 = pm.sample(tune=tune,
                       draws=draws,
                         cores=1)
```

```
Auto-assigning NUTS sampler...
Initializing NUTS using jitter+adapt_diag...
Sequential sampling (2 chains in 1 job)
NUTS: [sd, x, Intercept]
```

100.00% [3100/3100 00:08<00:00

Sampling chain 0, 0 divergences]

100.00% [3100/3100 00:14<00:00

Sampling chain 1, 0 divergences]

```
Sampling 2 chains for 600 tune and 2_500 draw iterations (1_200 + 5_00
0 draws total) took 24 seconds.
The acceptance probability does not match the target. It is 0.89764488
6027529, but should be close to 0.8. Try to increase the number of tun
ing steps.
```

In [33]:
```
trace_df2 = pm.trace_to_dataframe(trace2).assign(chain=lambda x: x.inc
trace_df2.shape
```

Out[33]: (5000, 4)

In [34]:
```
trace_df2.head()
```

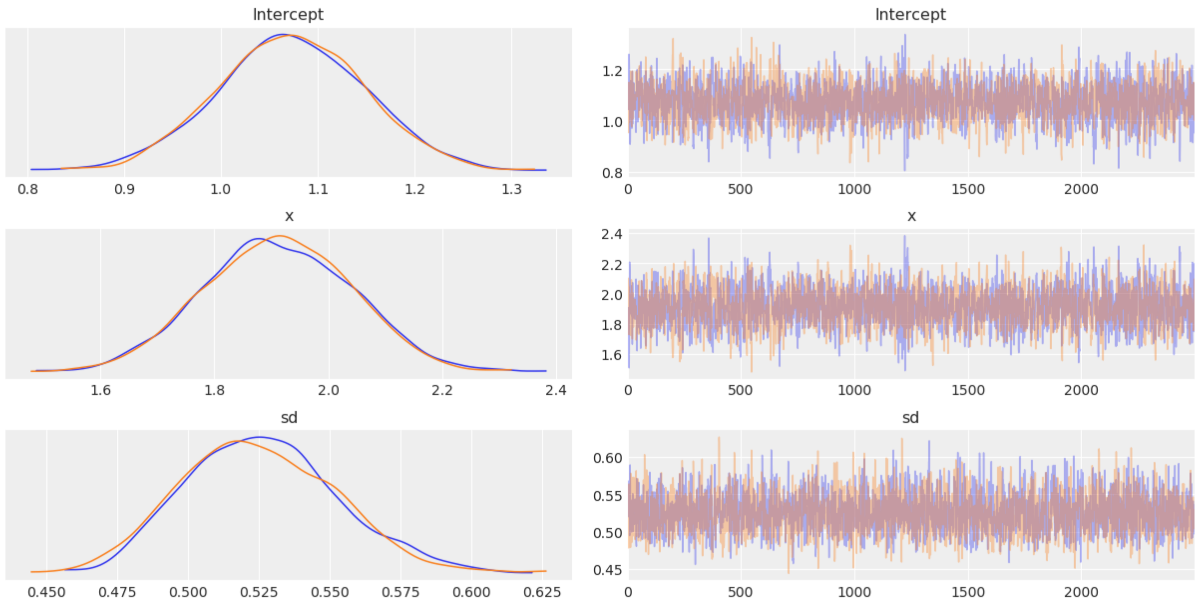
Out[34]:

	Intercept	x	sd	chain
0	1.139616	1.803427	0.527736	0
1	1.043334	1.877560	0.524002	0
2	1.126340	1.904954	0.567812	0
3	1.055079	1.857360	0.524943	0
4	1.136881	1.859635	0.520200	0

In [35]:
```
az.plot_trace(trace2, var_names=("Intercept", "x","sd"))
```

```
/Users/kenneth/anaconda3/lib/python3.7/site-packages/arviz/data/io_pym
c3.py:91: FutureWarning: Using `from_pymc3` without the model will be
deprecated in a future release. Not using the model will return less a
ccurate and less useful results. Make sure you use the model argument
or call from_pymc3 within a model context.
  FutureWarning,
```

Out[35]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x137802400>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x138991eb8
>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x1388bec50>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x13893e208
>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x1389fa668>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x138a41ef0
>]],
      dtype=object)
```



Prior and Posterior Predictive Checks

In [36]:
```
size = 200
beta0 = 0.5
```

```
beta1 = 3
test=pd.DataFrame()
test["x"]=np.linspace(-10, 10, size)
test["mu"]=beta0 + beta1 * data["x"]
test["y"]=data["mu"]+np.random.normal(scale=6, size=size)
```

In [37]:

```
test["x"].values.mean().round(2),test["x"].values.std().round(2)
```

Out[37]: (0.0, 5.8)

In [38]:

```
test["y"].values.mean().round(2),test["y"].values.std().round(2)
```

Out[38]: (2.58, 5.61)

In [39]:

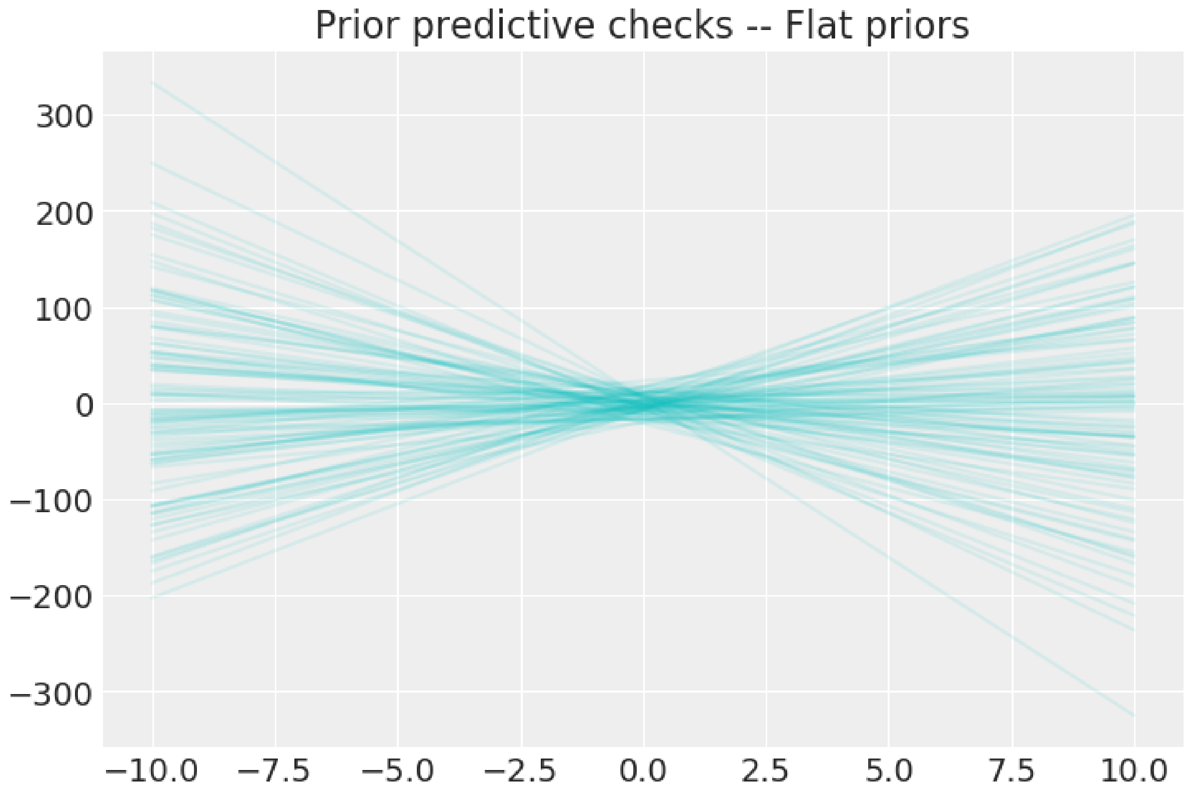
```
with pm.Model() as test_model:
    beta0 = pm.Normal("b0", 0.0, 10.0)
    beta1 = pm.Normal("b1", 0.0, 10.0)

    mu = beta0 + beta1 *test["x"]
    std = pm.Exponential("sd", 1.0)

    output = pm.Normal("obs", mu=mu, sigma=std, observed=test["y"])
```

In [40]:

```
with test_model:
    prior_checks = pm.sample_prior_predictive(samples=100, random_seec
```

In [41]:

```
for intercept, slobe in zip(prior_checks["b0"], prior_checks["b1"]):
    y =intercept+ slobe *test["x"]
    plt.plot(test["x"], y, c="c", alpha=0.1)

plt.title("Prior predictive checks -- Flat priors");
```



In [42]:

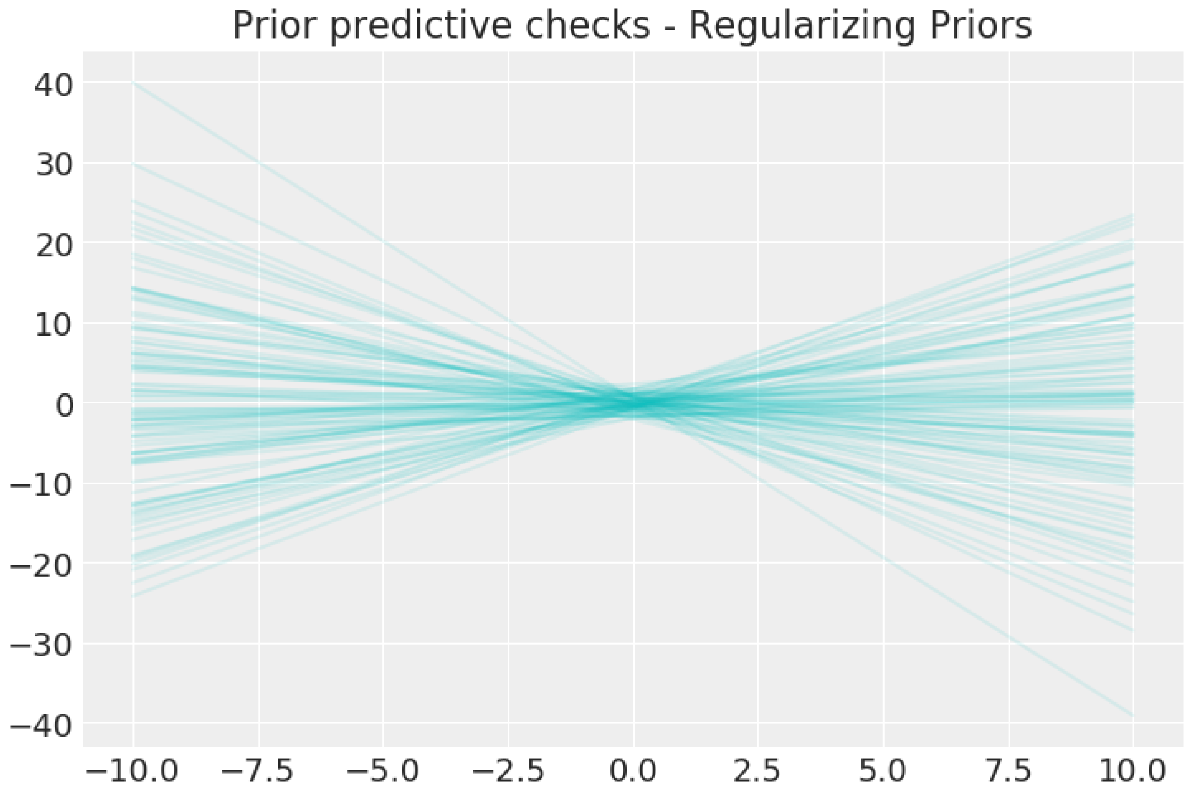
```
with pm.Model() as test_model:
    beta0 = pm.Normal("b0", 0.0, 1.0)
    beta1 = pm.Normal("b1", 0.0, 1.2)

    mu = beta0 + beta1 *test["x"]
    std = pm.Exponential("sd", 1.0)

    output = pm.Normal("obs", mu=mu, sigma=std, observed=test["y"])
```

In [43]:

```
with test_model:
    prior_checks = pm.sample_prior_predictive(samples=100, random_seec
```

In [44]:

```
for intercept, slobe in zip(prior_checks["b0"], prior_checks["b1"]):
    y =intercept+ slobe *test["x"]
    plt.plot(test["x"], y, c="c", alpha=0.1)

plt.title("Prior predictive checks - Regularizing Priors");
```



In [37]:
```
import arviz as az
```

In [46]:
```
with test_model:
    test_trace = pm.sample(draws=1000, tune=2000, random_seed=80)
az.plot_trace(test_trace)
```

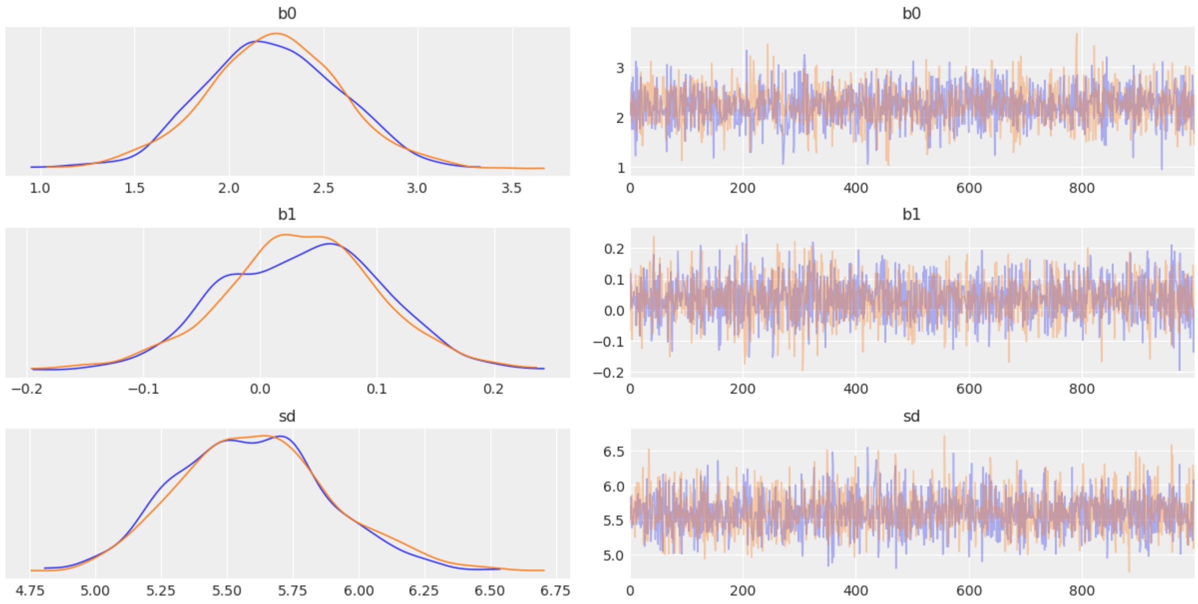
```
Auto-assigning NUTS sampler...
Initializing NUTS using jitter+adapt_diag...
Multiprocess sampling (2 chains in 2 jobs)
NUTS: [sd, b1, b0]
```

100.00% [6000/6000 00:14<00:00

Sampling 2 chains, 0 divergences]

```
Sampling 2 chains for 2_000 tune and 1_000 draw iterations (4_000 + 2_
000 draws total) took 30 seconds.
/Users/kenneth/anaconda3/lib/python3.7/site-packages/arviz/data/io_pym
c3.py:91: FutureWarning: Using `from_pymc3` without the model will be
deprecated in a future release. Not using the model will return less a
ccurate and less useful results. Make sure you use the model argument
or call from_pymc3 within a model context.
  FutureWarning,
```

Out[46]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x13c98e4e0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x139579898
>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x1377ec940>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x138b88c50
>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x13c8d52b0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x13958a2e8
>]],
      dtype=object)
```



In [47]:
```
test_trace_df=pd.DataFrame(list(test_trace))
test_trace_df.shape
```

Out[47]: (1000, 4)

In [48]:
```
test_trace_df.head()
```

Out[48]:

	b0	b1	sd	sd_log__
0	2.600583	-0.067051	5.445861	1.694856
1	2.081988	0.132699	5.695350	1.739650
2	2.294409	0.004839	5.526605	1.709574
3	1.891478	0.082070	5.501144	1.704956
4	2.179933	-0.095898	5.858490	1.767892

In [49]:
```
with test_model:
    ppc = pm.sample_posterior_predictive(
        test_trace, var_names=["b0", "b1", "obs"], random_seed=100
    )
```

100.00% [2000/2000 00:07<00:00]

In [50]:
```
ppc["b0"].shape,ppc["b1"].shape,ppc["obs"].shape
```

Out[50]: ((2000,), (2000,), (2000, 200))

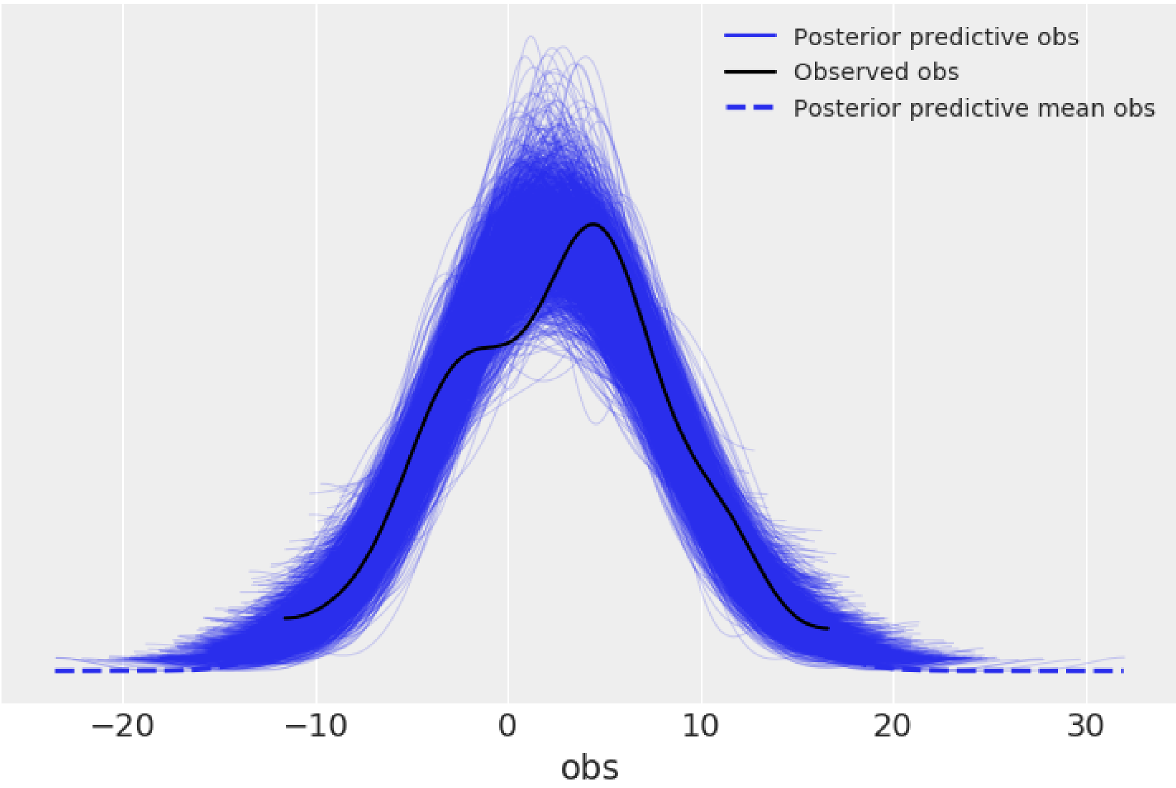
In [51]:
```
ppc["obs"].shape
```

Out[51]: (2000, 200)

In [52]:
```
visual_data = az.from_pymc3(test_trace, posterior_predictive=ppc)
az.plot_ppc(visual_data)
```

```
/Users/kenneth/anaconda3/lib/python3.7/site-packages/arviz/data/io_pym
c3.py:91: FutureWarning: Using `from_pymc3` without the model will be
deprecated in a future release. Not using the model will return less a
ccurate and less useful results. Make sure you use the model argument
or call from_pymc3 within a model context.
  FutureWarning,
```

Out[52]: <matplotlib.axes._subplots.AxesSubplot at 0x1396f4dd8>



Robust Regression with Fat tails

In [53]:
```
size = 100
beta1 = 5
beta0 = 0.5
data2=pd.DataFrame()
data2["x"] = np.linspace(0, 1, size)
data2["mu"]= beta0 + beta1*data2["x"]
data2["y"]=data2["mu"]+np.random.normal(scale=.5, size=size)
print(data2.shape)
# next we add three outliers
temp=pd.DataFrame()
temp["x"]= [.1, .15, .2]
temp["y"]=[8, 6, 9]
temp["mu"]=beta0 + beta1*temp["x"]
data2=pd.concat([data2,temp])
data2.shape
```

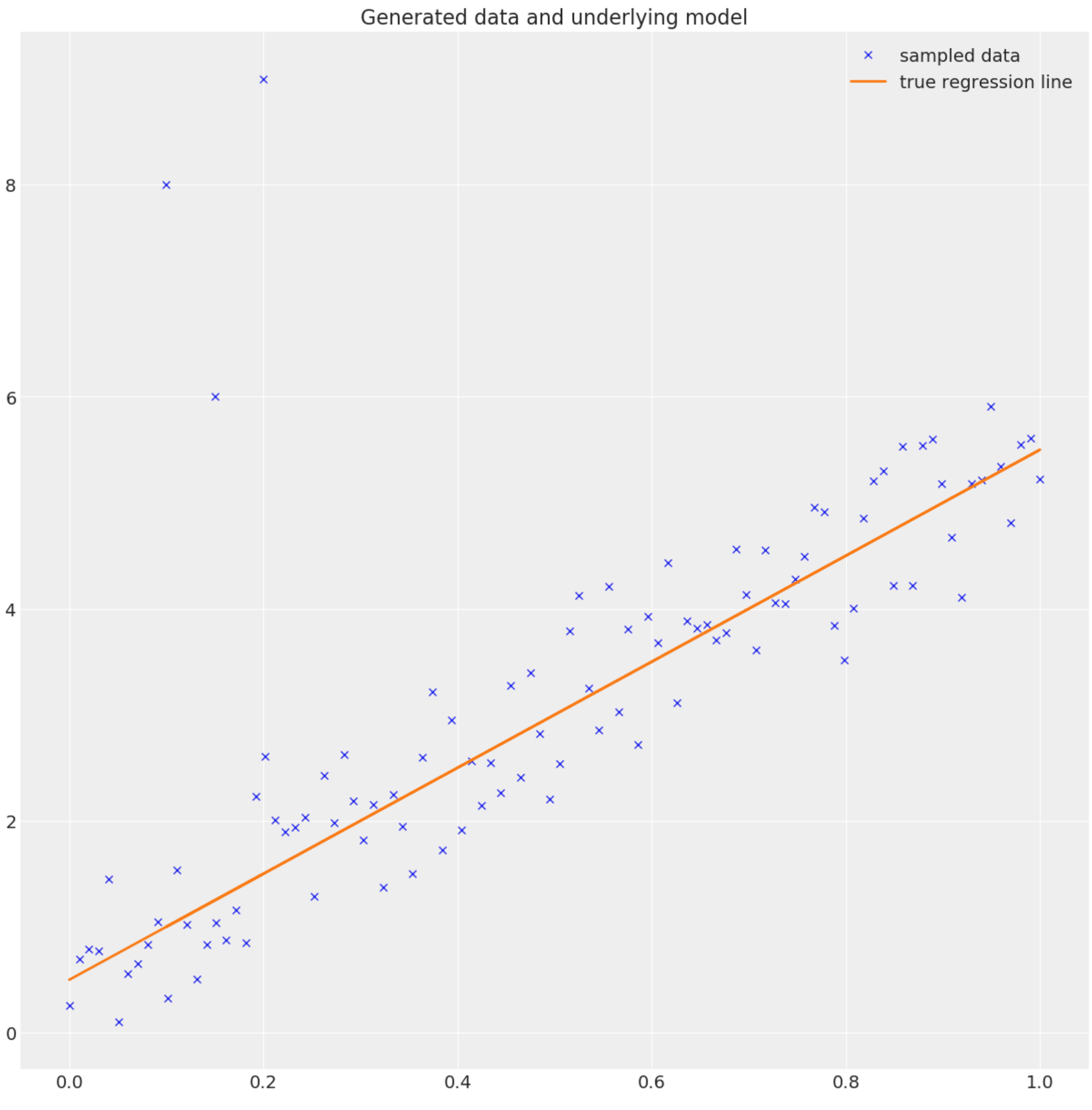
```
(100, 3)
/Users/kenneth/anaconda3/lib/python3.7/site-packages/ipykernel_launche
r.py:14: FutureWarning: Sorting because non-concatenation axis is not
```

```
aligned. A future version
of pandas will change to not sort by default.

To accept the future behavior, pass 'sort=False'.

To retain the current behavior and silence the warning, pass 'sort=Tru
e'.
```

Out[53]:
```
(103, 3)
```

In [54]:
```
fig = plt.figure(figsize=(12, 12))
plt.title('Generated data and underlying model')
plt.plot(data2["x"], data2["y"], 'x', label='sampled data')
plt.plot(data2["x"], data2["mu"], label='true regression line', lw=2.)
plt.legend(loc=0)
```

Out[54]:
```
<matplotlib.legend.Legend at 0x1413b5518>
```



describe the linear model and adds a Normal likelihood by default.

In [55]:
```
with pm.Model() as model:
    pm.GLM.from_formula('y ~ x', data2)
```

```
    trace3 = pm.sample(tune=1000)
```

```
Auto-assigning NUTS sampler...
Initializing NUTS using jitter+adapt_diag...
Multiprocess sampling (2 chains in 2 jobs)
NUTS: [sd, x, Intercept]
```

100.00% [4000/4000 00:09<00:00

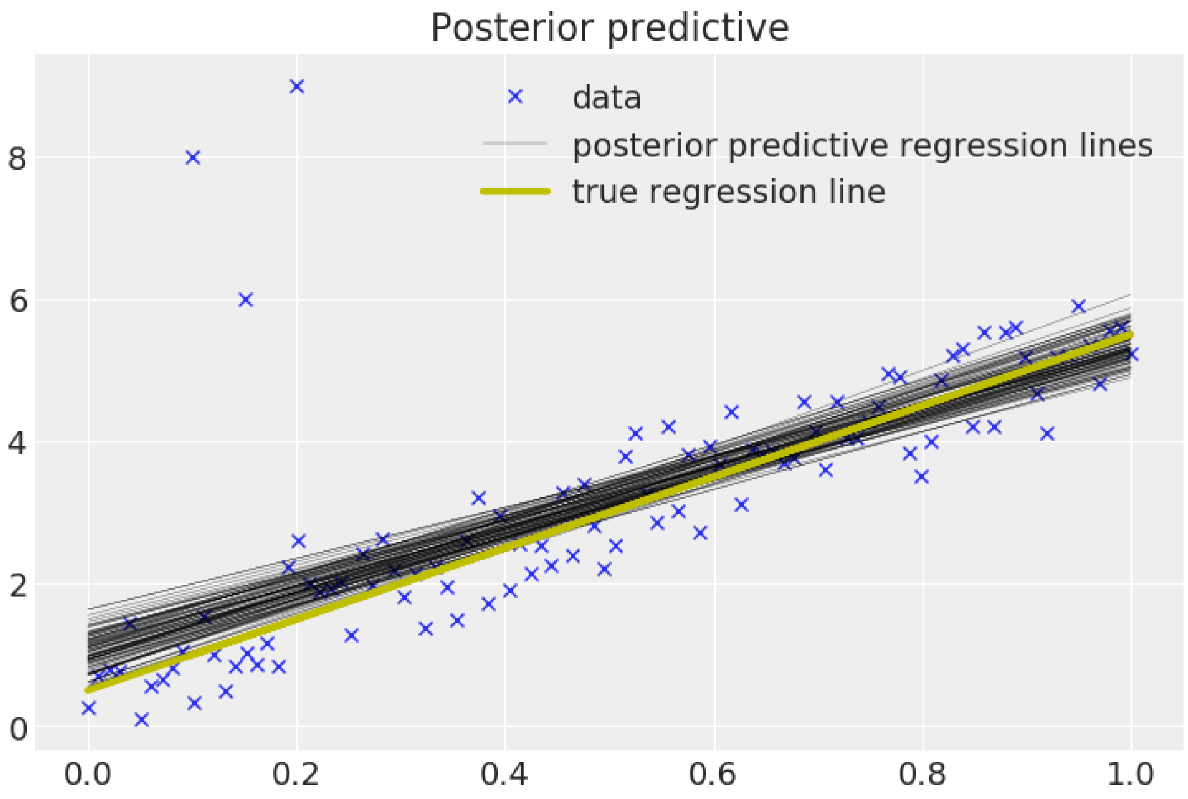
Sampling 2 chains, 0 divergences]

```
Sampling 2 chains for 1_000 tune and 1_000 draw iterations (2_000 + 2_
000 draws total) took 21 seconds.
```

In [56]:

```
plt.plot(data2["x"], data2["y"], 'x', label='data')
pm.plot_posterior_predictive_glm(trace3, samples=100,
                                 label='posterior predictive regressio
plt.plot(data2["x"], data2["mu"],
         label='true regression line', lw=3., c='y')

plt.legend(loc=0)
```

Out[56]: <matplotlib.legend.Legend at 0x13f90c278>



In [57]:

```
with pm.Model() as  robust_model:
    f = pm.glm.families.StudentT()
    pm.GLM.from_formula('y ~ x', data2, family=f)
    robust_trace = pm.sample(tune=2000)
```

```
Auto-assigning NUTS sampler...
Initializing NUTS using jitter+adapt_diag...
Multiprocess sampling (2 chains in 2 jobs)
NUTS: [lam, x, Intercept]
```

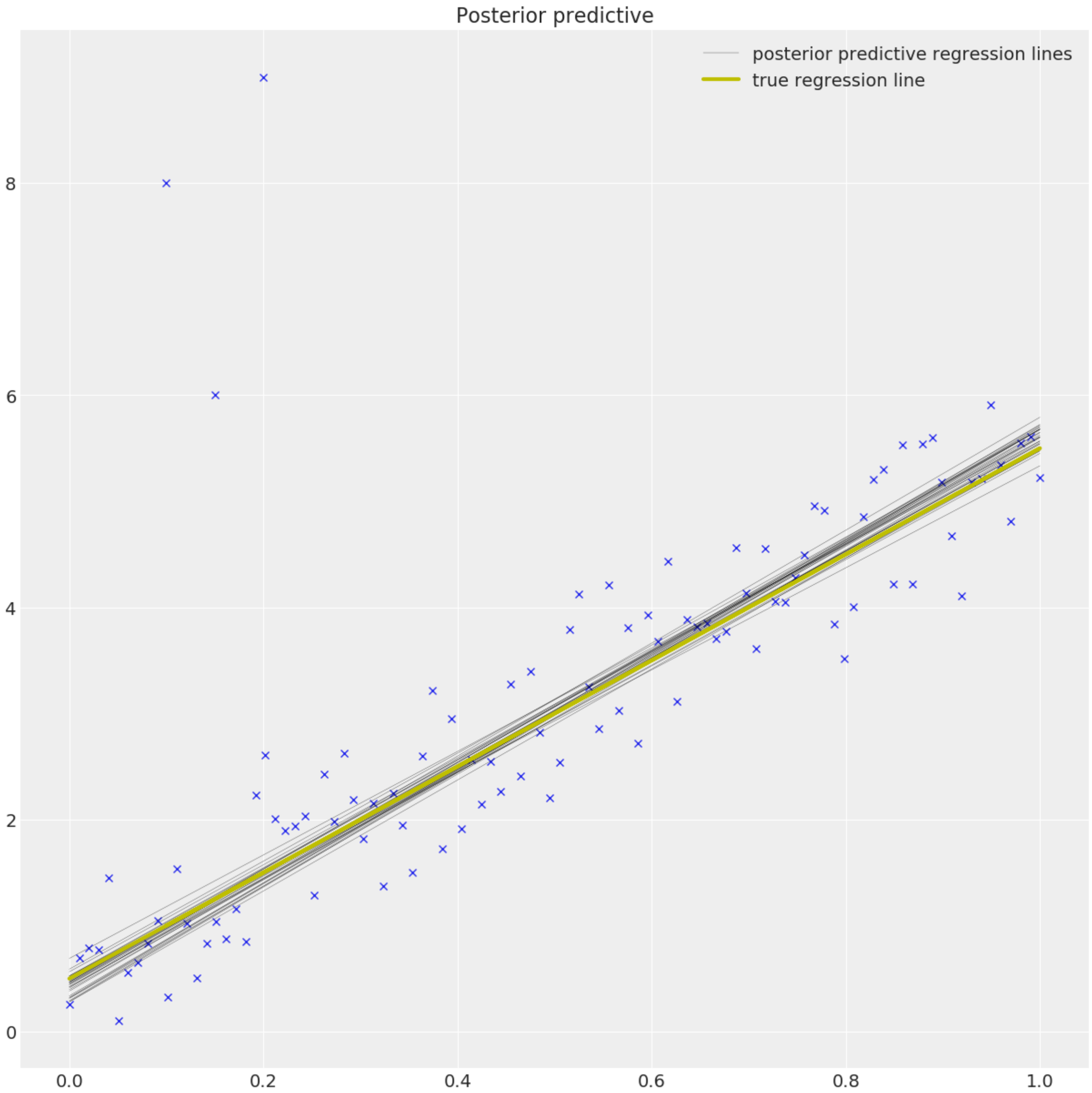
100.00% [6000/6000 00:17<00:00

Sampling 2 chains, 0 divergences]

```
Sampling 2 chains for 2_000 tune and 1_000 draw iterations (4_000 + 2_
000 draws total) took 25 seconds.
```

In [58]:

```
plt.figure(figsize=(12, 12))
plt.plot(data2["x"], data2["y"], 'x')
pm.plots.plot_posterior_predictive_glm(robust_trace,
                                       label='posterior predictive reg
plt.plot(data2["x"], data2["mu"],
         label='true regression line', lw=3., c='y')
plt.legend();
```



In [59]:

```
with pm.Model() as my_model:


    std = pm.HalfCauchy('sigma', beta=10, testval=1)
    beta0 = pm.Normal('Intercept', 0, sd=20)
    beta1 = pm.Normal('slope', 0, sd=20)
    df = pm.Exponential('df', 1 / 29,testval=5) + 2.# make the df is a
    # testval is the initial value to start sample.
    # likelihood
```

```
    likelihood = pm.StudentT('y',nu=df, mu=beta0 + beta1 *data2["x"],
```

In [60]:
```
tune = 2000
draws = 2000
with my_model:
    my_trace = pm.sample(tune=tune,
                         draws=draws,
                         chains=4)
```

```
Auto-assigning NUTS sampler...
Initializing NUTS using jitter+adapt_diag...
Multiprocess sampling (4 chains in 2 jobs)
NUTS: [df, slope, Intercept, sigma]
```

100.00% [16000/16000

00:34<00:00 Sampling 4 chains, 0 divergences]

```
Sampling 4 chains for 2_000 tune and 2_000 draw iterations (8_000 + 8_
000 draws total) took 58 seconds.
```

In [61]:
```
my_output=pd.DataFrame(list(my_trace))
my_output.head()
```

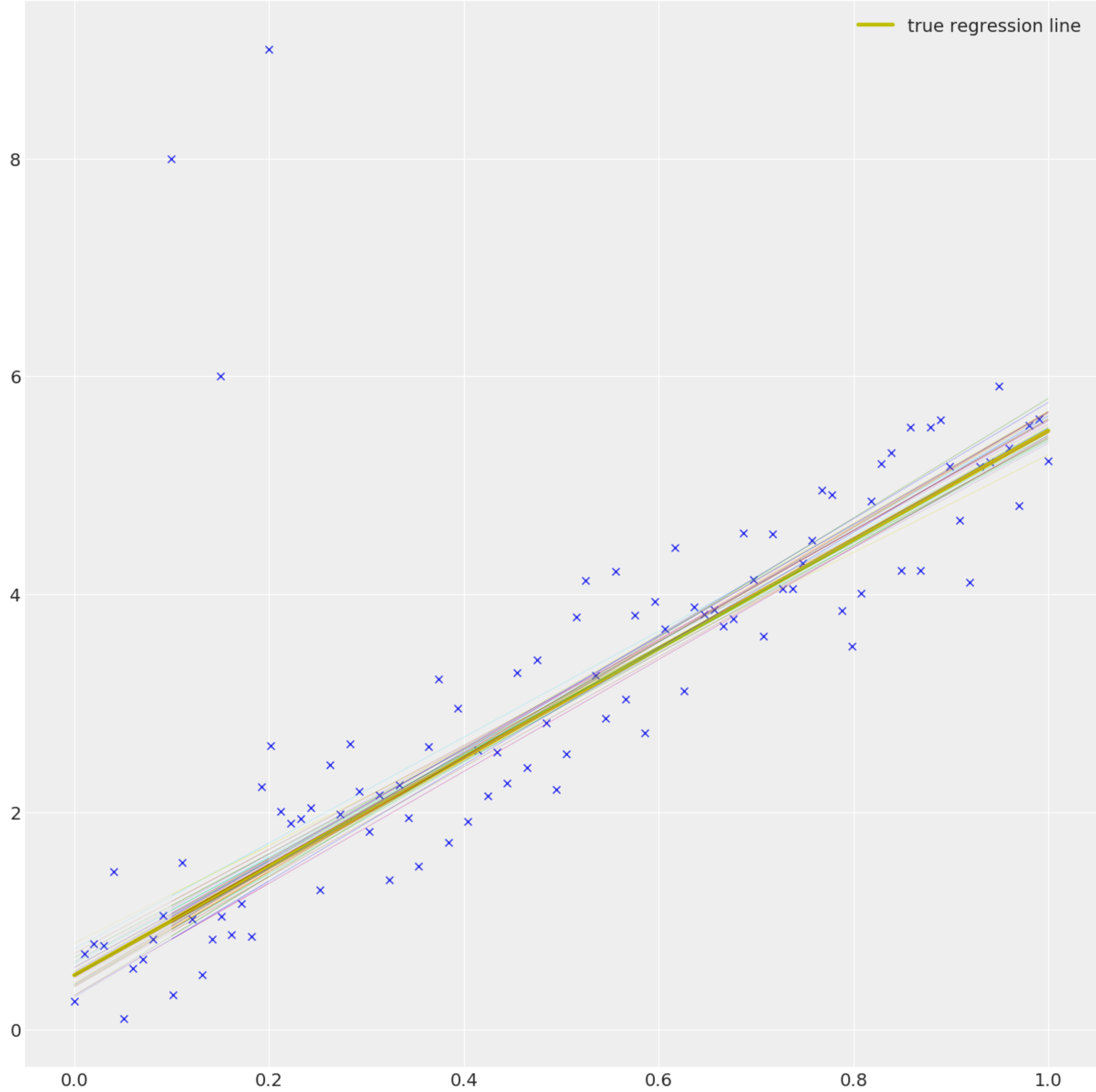
Out[61]:

	Intercept	df	df_log__	sigma	sigma_log__	slope
0	0.310019	0.215443	-1.535058	0.414028	-0.881822	5.178114
1	0.542920	0.228237	-1.477369	0.403174	-0.908388	5.049034
2	0.423048	0.198153	-1.618714	0.390685	-0.939854	5.082750
3	0.427799	0.216678	-1.529342	0.417152	-0.874305	4.943569
4	0.492572	0.079540	-2.531499	0.378457	-0.971652	4.980386

Randomly select 100 rows. We randomly take 100 indices.

In [62]:
```
listindex=pd.Series(my_output.index).sample(30).values
```

In [63]:
```
plt.figure(figsize=(12, 12))
plt.plot(data2["x"], data2["y"], 'x')
plt.plot(data2["x"], data2["mu"],
         label='true regression line', lw=3., c='y')

for l in listindex:
    plt.plot(data2["x"],my_output.loc[l,"Intercept"]+my_output.loc[l,'

plt.legend();
```



Bayesian Regression In Real Data

In [28]:
```
google.shape
```

Out[28]: (1446, 7)

In [29]:
```
google["Y"]=google["Close"].shift(-1)-google["Close"] # the price char
```

In [30]:
```
# Next we build some predictors
google["X1"]=(google["Close"]-google["Close"].shift(3))/3
google["X2"]=(google["Close"]-google["Close"].shift(6))/6
google["X3"]=(google["Close"]-google["Close"].shift(9))/9
google["X4"]=(google["Close"]-google["Close"].shift(12))/12
google["X5"]=(google["Close"]-google["Close"].shift(15))/15
google.dropna(inplace=True)
```

In [31]:
```
google.head()
```

Out[31]:

Date	Open	High	Low	Close	Adj Close	Volume	
2015-01-26	537.055542	537.524231	528.219788	533.744629	533.744629	1543700	-0.0
2015-01-27	528.518921	529.246948	516.771179	517.210022	517.210022	1904000	-0.0
2015-01-28	521.348633	521.558044	508.603638	508.603638	508.603638	1683800	-0.0
2015-01-29	509.600891	509.690643	499.827728	509.261810	509.261810	4186300	0.0
2015-01-30	514.447571	538.391846	514.108521	533.056519	533.056519	5606300	0.0

In [32]:

```
google.shape
```

Out[32]: (1430, 13)

In [33]:

```
n = google.shape[0]
n_train =  (int)(0.8 * n)
train = google[0:n_train]
test = google[n_train+1:n]
```

In [34]:

```
with pm.Model() as stock_prediction: # model specification

    # Define priors
    std = pm.HalfCauchy('sigma', beta=20, testval=1) # unique name for
    intercept = pm.Normal('intercept', 0, sd=10)
    b1 = pm.Normal('b1', 0, sd=10)
    b2 = pm.Normal('b2', 0, sd=10)
    b3 = pm.Normal('b3', 0, sd=10)
    b4 = pm.Normal('b4', 0, sd=10)
    b5 = pm.Normal('b5', 0, sd=10)
    df = pm.Exponential('df', 1 / 29,testval=5) + 2.# make the df is a
    # Define likelihood
    likelihood =  pm.StudentT('y',nu=df, mu=intercept
                          + b1 * train["X1"]
                          +b2*train["X2"]
                          +b3*train["X3"]
                          +b4*train["X4"]
                          +b5*train["X5"],
                          sd=std,
                          observed=train["Y"])
```

In [41]:

```
with stock_prediction:
    # Inference
```

```
    tune = 2000
    draws = 2000
    trace = pm.sample( tune=tune,
                       draws=draws,
                       cores=4)
```

```
Auto-assigning NUTS sampler...
Initializing NUTS using jitter+adapt_diag...
Multiprocess sampling (4 chains in 4 jobs)
NUTS: [df, b5, b4, b3, b2, b1, intercept, sigma]
```

100.00% [16000/16000 01:07<00:00 Sampling 4 chains, 0 divergences]

```
Sampling 4 chains for 2_000 tune and 2_000 draw iterations (8_000 + 8_
000 draws total) took 92 seconds.
```

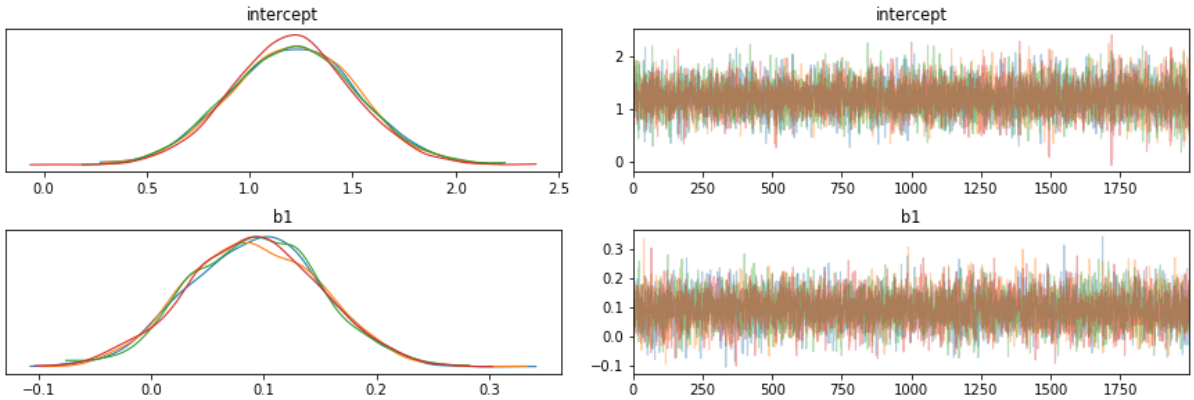
In [42]:

```
az.plot_trace(trace,var_names=("intercept","b1"))
```

```
/Users/kenneth/anaconda3/lib/python3.7/site-packages/arviz/data/io_pym
c3.py:91: FutureWarning: Using `from_pymc3` without the model will be
deprecated in a future release. Not using the model will return less a
ccurate and less useful results. Make sure you use the model argument
or call from_pymc3 within a model context.
  FutureWarning,
```

Out[42]:

```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x13cd6e7f0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x13c6593c8
>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x13ca3db38>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x13ca25cc0
>]],
      dtype=object)
```



In [43]:

```
trace_df = pm.trace_to_dataframe(trace).assign(chain=lambda x: x.index
trace_df.shape
```

Out[43]: (8000, 9)

In [44]:

```
trace_df.head()
```

Out[44]:

	intercept	b1	b2	b3	b4	b5	sigma	
0	0.474411	0.158385	-0.289336	0.220426	-0.644852	0.127532	9.099647	1.228
1	0.530339	0.147792	-0.228153	0.255927	-0.468799	0.024782	8.849960	1.157

	intercept	b1	b2	b3	b4	b5	sigma	
2	1.624239	0.019882	-0.035750	0.119056	-0.796117	0.436116	8.278345	1.028
3	1.353486	0.093426	-0.068033	0.153352	-0.675423	0.166378	8.713457	0.858
4	1.886662	0.062652	-0.235952	0.016597	-0.355979	-0.037765	8.231791	1.097

In [45]:

```
train.head()
```

Out[45]:

	Open	High	Low	Close	Adj Close	Volume	
Date							
2015-01-26	537.055542	537.524231	528.219788	533.744629	533.744629	1543700	-0.0
2015-01-27	528.518921	529.246948	516.771179	517.210022	517.210022	1904000	-0.0
2015-01-28	521.348633	521.558044	508.603638	508.603638	508.603638	1683800	-0.0
2015-01-29	509.600891	509.690643	499.827728	509.261810	509.261810	4186300	0.0
2015-01-30	514.447571	538.391846	514.108521	533.056519	533.056519	5606300	0.0

in-sample

In [46]:

```
traceindex=pd.Series(trace_df.index)
train["predictedPrice"]=0
train["predictedDifference"]=0
for day in train.index:
    listindex=traceindex.sample(100).values
    total=[]
    for m in listindex:
        total.append(trace_df.loc[m,"intercept"]
             +trace_df.loc[m,"b1"]*train.loc[day,"X1"]
             +trace_df.loc[m,"b2"]*train.loc[day,"X2"]
             +trace_df.loc[m,"b3"]*train.loc[day,"X3"]
             +trace_df.loc[m,"b4"]*train.loc[day,"X4"]
             +trace_df.loc[m,"b5"]*train.loc[day,"X5"]
                    )
    train.loc[day,"predictedDifference"]=np.array(total).mean()
    train.loc[day,"predictedPrice"]= train.loc[day,"Close"] +train.loc
```

```
/Users/kenneth/anaconda3/lib/python3.7/site-packages/ipykernel_launche
r.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
```

```
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy

/Users/kenneth/anaconda3/lib/python3.7/site-packages/ipykernel_launche
r.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy
  This is separate from the ipykernel package so we can avoid doing im
ports until
/Users/kenneth/anaconda3/lib/python3.7/site-packages/pandas/core/index
ing.py:543: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy
  self.obj[item] = s
```

In [47]:

```
train["predictedDifference"].head()
```

Out[47]:

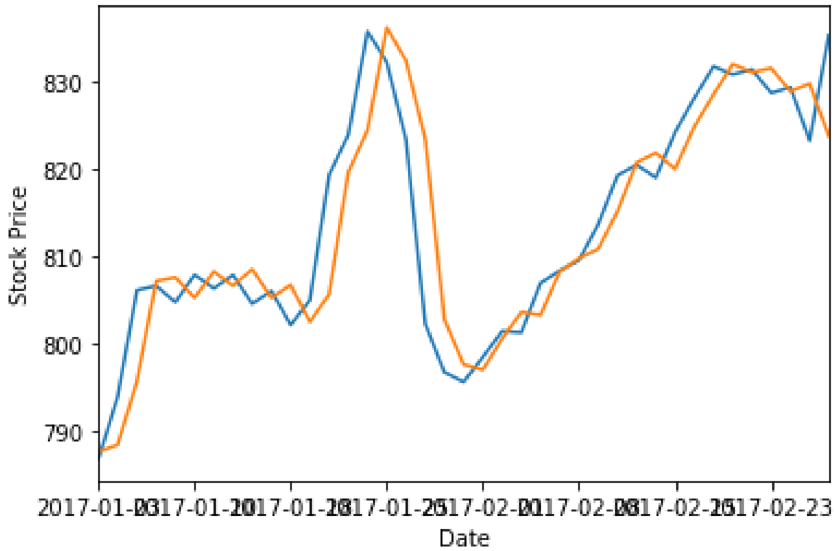
```
Date
2015-01-26    0.265991
2015-01-27    0.126875
2015-01-28   -0.199142
2015-01-29    0.105434
2015-01-30    0.701674
Name: predictedDifference, dtype: float64
```

In [94]:

```
(train.loc["2017-01-01":"2017-02-29","Close"] + train.loc["2017-01-01'
(train.loc["2017-01-01":"2017-02-29","Close"] + train.loc["2017-01-01'
plt.ylabel("Stock Price")
```

Out[94]:

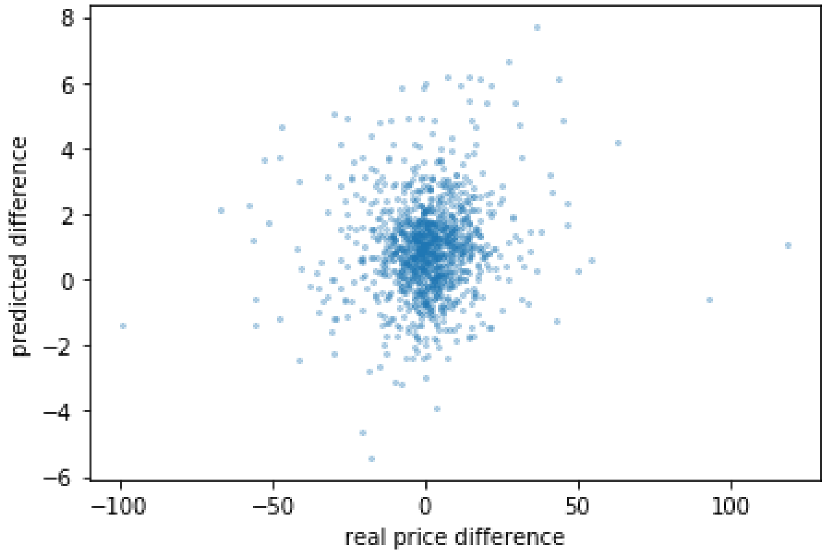
```
Text(0, 0.5, 'Stock Price')
```



In [69]:

```
plt.scatter(train["Y"],train["predictedDifference"], alpha=0.3, s=4)
plt.ylabel("predicted difference")
plt.xlabel("real price difference")
```

Out[69]: Text(0.5, 0, 'real price difference')



In [70]:
```
from sklearn.metrics import r2_score
r2_score(train["Y"],train["predictedDifference"])
```

Out[70]: 0.012268186265554 26

out-sample

In [71]:
```
traceindex=pd.Series(trace_df.index)
test["predictedPrice"]=0
test["predictedDifference"]=0
for day in test.index:
    listindex=traceindex.sample(100).values
    total=[]
    for m in listindex:
        total.append(trace_df.loc[m,"intercept"]
             +trace_df.loc[m,"b1"]*test.loc[day,"X1"]
             +trace_df.loc[m,"b2"]*test.loc[day,"X2"]
             +trace_df.loc[m,"b3"]*test.loc[day,"X3"]
             +trace_df.loc[m,"b4"]*test.loc[day,"X4"]
             +trace_df.loc[m,"b5"]*test.loc[day,"X5"]
                    )
    test.loc[day,"predictedDifference"]=np.array(total).mean()
    test.loc[day,"predictedPrice"]= test.loc[day,"Close"] +test.loc[da
```

```
/Users/kenneth/anaconda3/lib/python3.7/site-packages/ipykernel_launche
r.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy

/Users/kenneth/anaconda3/lib/python3.7/site-packages/ipykernel_launche
r.py:3: SettingWithCopyWarning:
```

```
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy
  This is separate from the ipykernel package so we can avoid doing im
ports until
/Users/kenneth/anaconda3/lib/python3.7/site-packages/pandas/core/index
ing.py:543: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy
  self.obj[item] = s
```

In [72]:

```
test["predictedDifference"].head()
```

Out[72]:

```
Date
2019-08-13    0.589717
2019-08-14    1.882693
2019-08-15    2.203070
2019-08-16    2.622890
2019-08-19    2.647646
Name: predictedDifference, dtype: float64
```

In [76]:

```
test["Y"].head()
```

Out[76]:

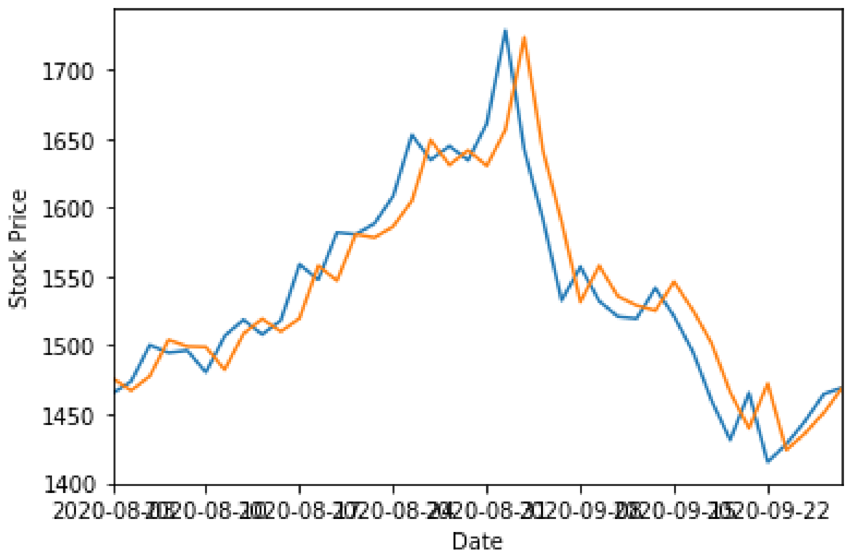
```
Date
2019-08-13   -32.979980
2019-08-14     2.969971
2019-08-15    10.339966
2019-08-16    20.849976
2019-08-19   -15.760010
Name: Y, dtype: float64
```

In [98]:

```
(test.loc["2020-08-01":"2020-09-29","Close"] + test.loc["2020-08-01":'
(test.loc["2020-08-01":"2020-09-29","Close"] + test.loc["2020-08-01":'
plt.ylabel("Stock Price")
```

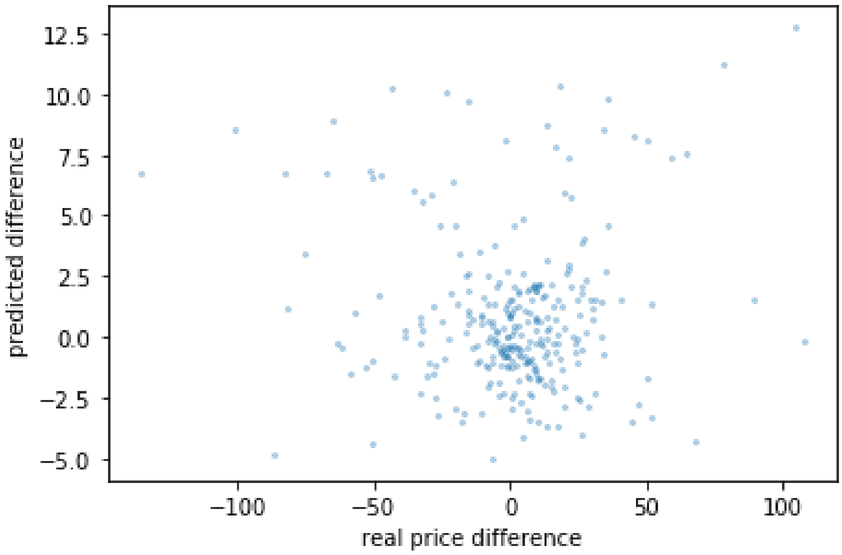
Out[98]:

```
Text(0, 0.5, 'Stock Price')
```



In [99]:
```
plt.scatter(test["Y"],test["predictedDifference"], alpha=0.3, s=4)
plt.ylabel("predicted difference")
plt.xlabel("real price difference")
```

Out[99]: Text(0.5, 0, 'real price difference')



In [100…
```
from sklearn.metrics import r2_score
r2_score(test["Y"],test["predictedDifference"])
```

Out[100… -0.015157710284178894

In [ ]: