lab05

June 12, 2021

1 Exercise 1

Linear models are an important class in data analysis problems. Your aim for this exercise is using such an approach modeling of !Kung people heights (applying Stan).

[1]:
```
from cmdstanpy import CmdStanModel
import arviz as az
import numpy as np
import scipy.stats as stats
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib as mpl
```

[2]:
```
_BASE_URL = "https://raw.githubusercontent.com/rmcelreath/rethinking/
 ↪Experimental/data"
HOWELL_DATASET_PATH = f"{_BASE_URL}/Howell1.csv"
d = pd.read_csv(HOWELL_DATASET_PATH, sep=';', header=0)
d=d[d.age>=18] #just adults for now
d.sort_values(by=['weight'],inplace=True)
d.head()
```

[2]:

	height	weight	age	male
210	143.510	31.071052	18.0	0
184	141.605	31.524644	19.0	1
373	142.240	31.666391	36.0	0
2	136.525	31.864838	65.0	0
244	146.050	31.864838	44.0	0

Using Stan create the linear model for presented data and interpret the results.

To create model for !Kung people's heights we need to get some information about how does heigh distribution tends to look like. From information avaliable online we can learn that distribution of heights like many other variables found in nature tends to be normaly distributed. So we can assume:

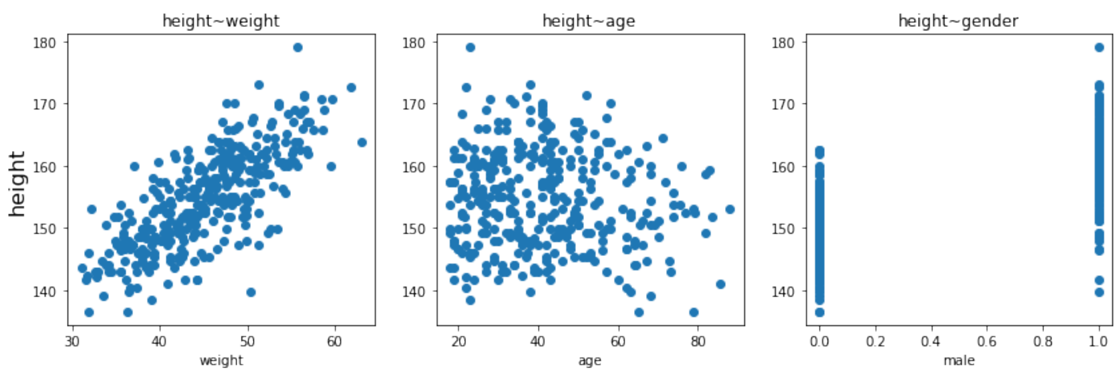
$$height \sim \text{Normal}(\mu, \sigma)$$

Using linear model approach we have to link mean of normal distribution seen above to some predictor variable as a linear function of this variable.

$$\mu = \alpha + \beta P_v,$$

where P_v is our choosen predictor variable. We'll plot our data against eatch otcher to better understand whitch predictor we should use.

[3]:
```
#Plotting heigh against other possible predictors in our data
fig, axes = plt.subplots(1, 3, figsize=(14, 4))
axes[0].scatter(d["weight"], d["height"]);
axes[0].set_ylabel("height", fontsize=16);
axes[0].set_title("height~weight")
axes[0].set_xlabel("weight");
axes[1].scatter(d["age"], d["height"]);
axes[1].set_title("height~age")
axes[1].set_xlabel("age");
axes[2].scatter(d["male"], d["height"]);
axes[2].set_xlabel("male");
axes[2].set_title("height~gender");
```



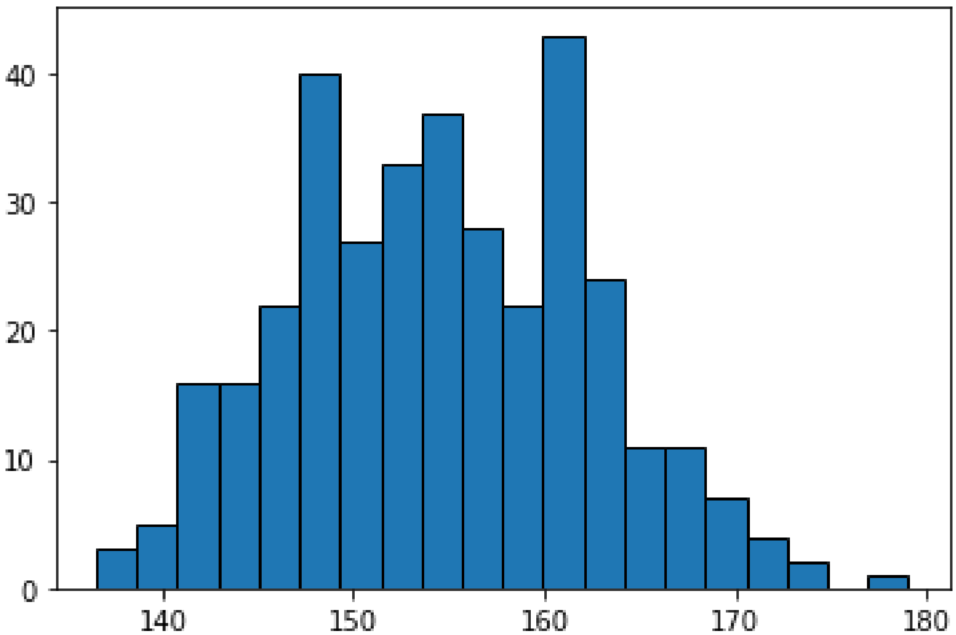
From all the possible predictors in our data, weight looks like the best option. So asserting P_v as weight our model looks like:

$$height \sim \text{Normal}(\mu, \sigma),$$

$$\mu = \alpha + \beta(w - \bar{w}),$$

Now we have to assert proper priors for α and β. For estimating α priors we can start by getting histogram of height data. Assuming predictor value has no impact ($\beta = 0$):

[4]:
```
fig, axes = plt.subplots()
axes.hist(d["height"], bins=20, edgecolor='black')
plt.show()
```



We can notice that it does look Gaussian in shape. Because we can't get any informatior to create informative priori on alpha like what heigh is favoured by natural selection in their environmet we have to use weakly informative priori. Let's use data from Botswana with lies near the teritories !Kung Sao people occupy. Mean heigh of women in Botswana is 160.9 cm while males is 170.9 cm. Botswana male to female ratio is around 94 males for 100 females so we can assume mean height is 166 cm. Setting variance as 20 seems reasonable. So that gives us model:

$$height \sim \mathrm{N}ormal(\mu, \sigma),$$

$$\mu = \alpha + \beta(w - \bar{w}),$$

$$\alpha \sim \mathrm{N}ormal(166, 20)$$

$$\sigma \sim \mathrm{U}niform(0, 20)$$

Now we have to estimate prior for β. Let's start by assuming $\beta \sim \mathrm{N}ormal(0, 2)$.

[5]:
```python
with open('prio1.stan', 'r') as file:
    print(file.read())
```

```
data {
  int N;
  real W[N];
}

generated quantities {
  real alpha = normal_rng(166,20);
  real beta = normal_rng(0,5);
  real<lower = 0> sigma = uniform_rng(0,20);
```

```
  real y_sim[N];
  for (k in 1:N) {
    y_sim[k] = normal_rng(beta*W[N]+alpha,sigma);
  }
}
```

[6]:
```python
weight = (d["weight"]-np.mean(d["weight"]))
model_prior_uni=CmdStanModel(stan_file='prio1.stan')
Wn=np.arange(d["weight"].min(), d["weight"].max(), 0.2).tolist()
W = Wn - np.mean(Wn)
data=dict(N=len(W),W=W)
sim=model_prior_uni.sample(data=data,
                     fixed_param=True,
                     iter_warmup=0,
                     chains=1)
```

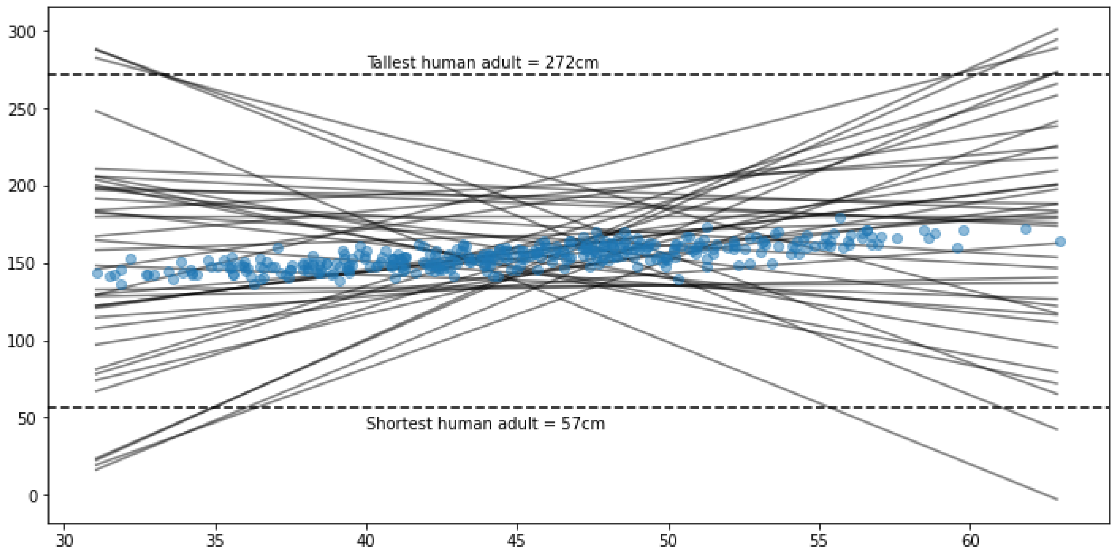
```
INFO:cmdstanpy:found newer exe file, not recompiling
INFO:cmdstanpy:compiled model file: /mnt/c/ola/DataAnalytics/lab05/prio1
INFO:cmdstanpy:start chain 1
INFO:cmdstanpy:finish chain 1
```

[7]:
```python
alpha_sim=sim.stan_variable('alpha')
beta_sim=sim.stan_variable('beta')
y_sim=sim.stan_variable('y_sim')

fig, ax = plt.subplots(figsize=(12, 6))
for i in range(40):
    ax.plot(Wn,alpha_sim[i]+beta_sim[i]*W, alpha=0.5,zorder=0, color='black')
ax.scatter(d.weight,d.height,alpha=0.5)
ax.axhline(272, color = 'black', linestyle='--')
ax.text(40,276,'Tallest human adult = 272cm')

ax.axhline(57, color = 'black', linestyle='--')
ax.text(40,43,'Shortest human adult = 57cm')

plt.show()
```



As we can see on plot above priors we've choosen poorly align with our knowledge about height-weight correlation. Seeing that it's impossible for people to get lighter as their height increase we can assume that it has to be > 0. To make it so we'll define beta as Log-Normal distribution. So our model looks like:

$$height \sim \text{Normal}(\mu, \sigma),$$

$$\mu = \alpha + \beta(w - \bar{w}),$$

$$\alpha \sim \text{Normal}(166, 20)$$

$\beta \sim \text{Log-}Normal(0, 1)$

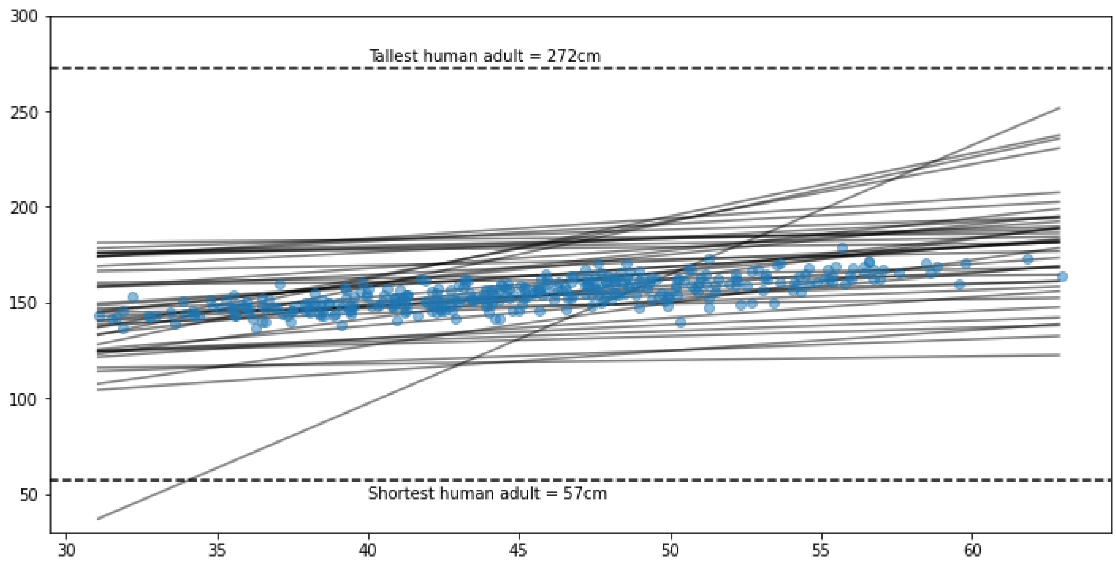
$$\sigma \sim \text{Uniform}(0, 20)$$

[8]:
```
model_prior_uni=CmdStanModel(stan_file='prio2.stan')
Wn = np.arange(d["weight"].min(), d["weight"].max(), 0.2).tolist()
W = Wn - np.mean(Wn)
data=dict(N=len(W),W=W)
sim=model_prior_uni.sample(data=data,
                           fixed_param=True,
                           iter_warmup=0,
                           chains=1)
alpha_sim=sim.stan_variable('alpha')
beta_sim=sim.stan_variable('beta')
y_sim=sim.stan_variable('y_sim')
```

```
INFO:cmdstanpy:found newer exe file, not recompiling
INFO:cmdstanpy:compiled model file: /mnt/c/ola/DataAnalytics/lab05/prio2
INFO:cmdstanpy:start chain 1
INFO:cmdstanpy:finish chain 1
```

[9]:
```
fig, ax = plt.subplots(figsize=(12, 6))
for i in range(40):
    ax.plot(Wn,alpha_sim[i]+beta_sim[i]*W, alpha=0.5,zorder=0,color = 'black')
ax.scatter(d.weight,d.height,alpha = 0.5)
ax.axhline(272, color = 'black', linestyle='--')
ax.text(40,276,'Tallest human adult = 272cm')

ax.axhline(57, color = 'black', linestyle='--')
ax.text(40,48,'Shortest human adult = 57cm')
ax.set_ylim([30 ,300])
plt.show()
```



We can observe that our priors look more sensible then before. Now using this priors we'll create model of height data. Our model:

$$height \sim \mathrm{Normal}(\mu, \sigma),$$

$$\mu = \alpha + \beta(w - \bar{w}),$$

$$\alpha \sim \mathrm{N}ormal(166, 20)$$

$\beta \sim \mathrm{Log}\text{-}Normal(0, 1)$

$$\sigma \sim \mathrm{U}niform(0, 20)$$

written using stan code looks like:

[10]:
```
with open('model1.stan', 'r') as file:
    print(file.read())
```

```
data {
  int N;
  vector[N] W;
  real h[N];
  int GL;
  vector[GL] gen;
}

parameters {
  real alpha;
  real beta;
  real<lower=0, upper=20> sigma;
}

transformed parameters {
  vector[N] mu;
  for (i in 1:N) {
    mu[i] = alpha + beta * (W[i]);
  }
}

model {
  alpha ~ normal(166,20);
  beta ~ lognormal(0,1);
  sigma ~ uniform(0,20);
  h ~ normal(mu, sigma);
}

generated quantities {
  real h_sim[GL];
  for (i in 1:GL) {
    h_sim[i] = normal_rng(alpha + beta*(gen[i]), sigma);
  }
}
```

[11]:
```
model_post1=CmdStanModel(stan_file='model1.stan')
weight = (d["weight"]-np.mean(d["weight"]))
w_sq=np.arange(d["weight"].min(), d["weight"].max(), 0.2)
to_get=(w_sq-np.mean(w_sq))
data=dict(N=len(weight), W=weight.tolist(), h=d.height.values, GL=len(to_get),␣
 ↪gen=to_get.tolist())
fit=model_post1.sample(data=data)
```

```
INFO:cmdstanpy:found newer exe file, not recompiling
INFO:cmdstanpy:compiled model file: /mnt/c/ola/DataAnalytics/lab05/model1
INFO:cmdstanpy:start chain 1
INFO:cmdstanpy:start chain 2
```

```
INFO:cmdstanpy:start chain 3
INFO:cmdstanpy:start chain 4
INFO:cmdstanpy:finish chain 2
INFO:cmdstanpy:finish chain 3
INFO:cmdstanpy:finish chain 4
INFO:cmdstanpy:finish chain 1
```

[12]:

```
az.summary(fit,var_names=['alpha','beta','sigma'],kind='stats')
```

[12]:

	mean	sd	hdi_3%	hdi_97%
alpha	154.596	0.272	154.110	155.134
beta	0.902	0.043	0.821	0.980
sigma	5.106	0.198	4.744	5.475

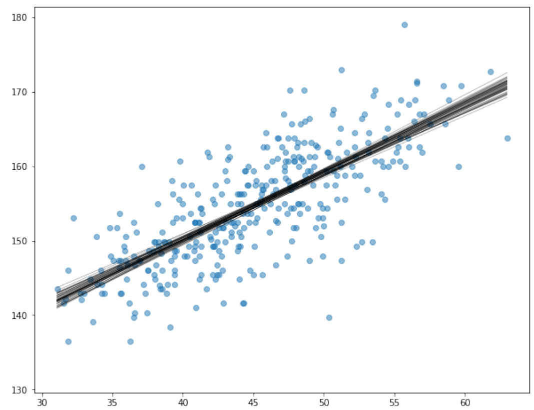
[13]:

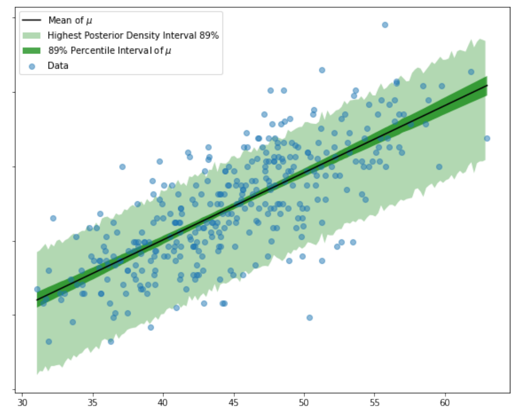
```
alpha_fit=fit.stan_variable('alpha')
beta_fit=fit.stan_variable('beta')
mu_fit=fit.stan_variable('mu')
h_sim=fit.stan_variable('h_sim')
hdi_height = az.hdi(h_sim, 0.89)
hdi_mu = az.hdi(mu_fit, 0.89)

fig, axes = plt.subplots(1,2, figsize=(22, 8),sharey=True,sharex=True)
axes[0].scatter(d.weight,d.height,alpha=0.5)
for i in range(50):
    axes[0].plot(d.weight, alpha_fit[i]+beta_fit[i]*weight, color = 'black',␣
 ↪alpha=0.5,linewidth=0.5)

axes[1].fill_between(w_sq, hdi_height[:,0], hdi_height[:,1], facecolor='green',␣
 ↪alpha=0.3);
axes[1].fill_between(d.weight.values, hdi_mu[:,0], hdi_mu[:,1],␣
 ↪facecolor='green', alpha=0.7);
axes[1].scatter(d.weight,d.height,alpha=0.5)
axes[1].plot(d.weight.values, np.mean(mu_fit,0), color='black')
axes[1].legend(['Mean of $\mu$', 'Highest Posterior Density Interval 89%', '89%␣
 ↪Percentile Interval of $\mu$', 'Data'])
plt.show()
```

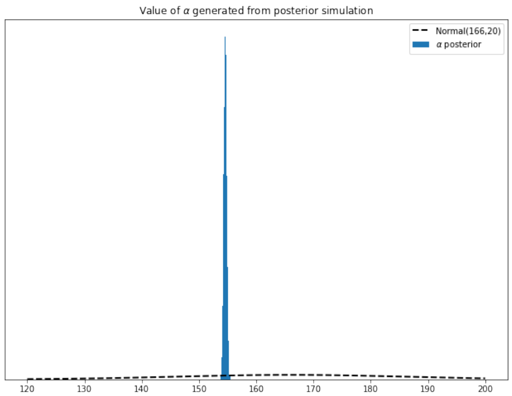
```
/mnt/c/Users/jkurek1/Desktop/DataAnalytics/venv/lib/python3.6/site-
packages/arviz/stats/stats.py:459: FutureWarning: hdi currently interprets 2d
data as (draw, shape) but this will change in a future release to (chain, draw)
for coherence with other functions
  FutureWarning,
```

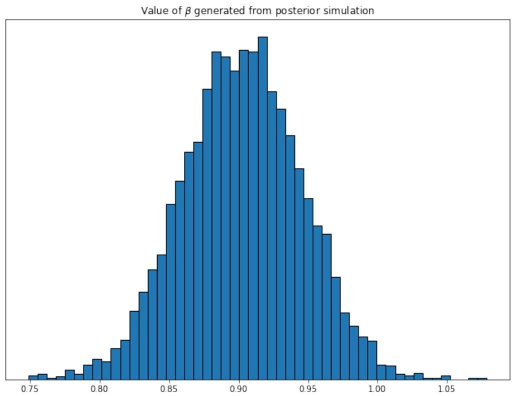




[14]:
```
fig, ax = plt.subplots(1,2, figsize=(24, 8))
ax[0].hist(alpha_fit, bins=50, density=True)
x=np.linspace(120,200,1000)
ax[0].set_title(r'Value of $\alpha$ generated from posterior simulation')
ax[0].plot(x, stats.norm.pdf(x, 166, 20), color='black', linestyle='dashed',␣
 ↪linewidth=2)
ax[0].legend(['Normal(166,20)',r'$\alpha$ posterior'])
ax[0].set_yticks([])

ax[1].hist(beta_fit, bins=50, density=True,edgecolor='black')
ax[1].set_title(r'Value of $\beta$ generated from posterior simulation')
ax[1].set_yticks([])
plt.show()
```





2 Exercise 2

Extend model of !Kung people height for the full dataset (including children) and discuss the results.

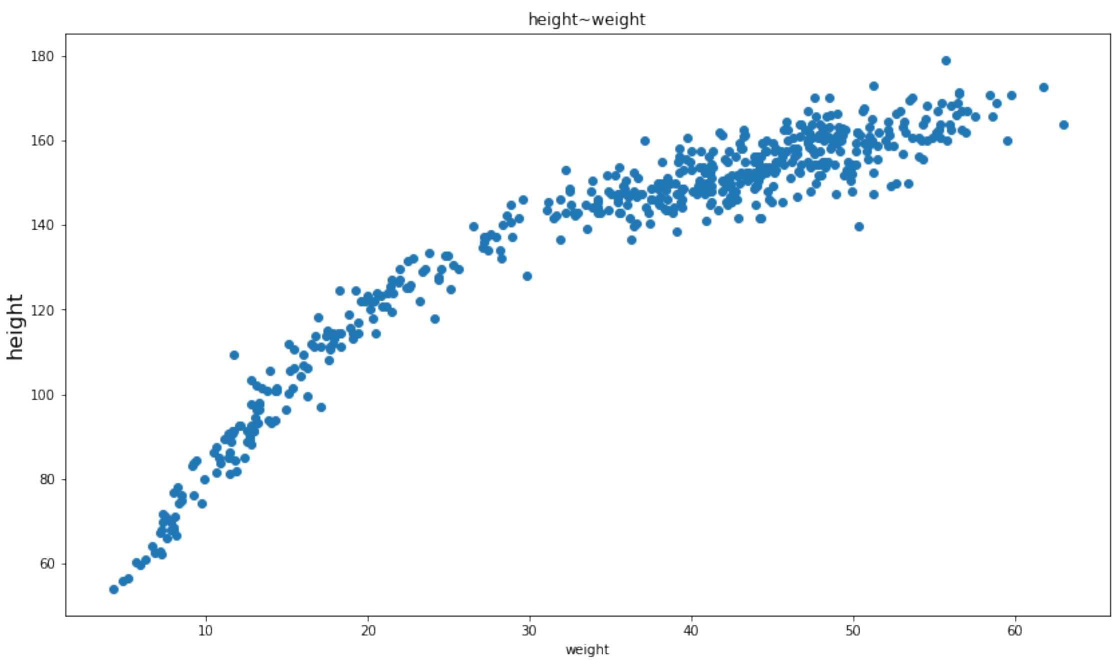
[15]:
```
_BASE_URL = "https://raw.githubusercontent.com/rmcelreath/rethinking/
  ↪Experimental/data"
HOWELL_DATASET_PATH = f"{_BASE_URL}/Howell1.csv"
d = pd.read_csv(HOWELL_DATASET_PATH, sep=';', header=0)
d.sort_values(by=['weight'],inplace=True)
d.head()
```

[15]:

	height	weight	age	male
517	53.9750	4.252425	0.0	0
466	55.8800	4.847764	0.0	0
519	56.5150	5.159609	0.0	0
354	60.4520	5.669900	1.0	1
325	59.6138	5.896696	1.0	0

Let's plot data for all of !Kung Sao people, including children. Just like in previous example we'll be using weight as a predictor variable.

[16]:
```
#Plotting heigh against other possible predictors in our data
fig, axes = plt.subplots(figsize=(14, 8))
axes.scatter(d["weight"], d["height"]);
axes.set_ylabel("height", fontsize=16);
axes.set_title("height~weight")
axes.set_xlabel("weight");
```



From the plot above we can tell that linear regression is not going to be enought, we'll have to use polynomial regression to build better curve association. Still we can use our model created for linear regression to see how it's gonna behave for full data set.

[17]:
```
weight = (d["weight"]-np.mean(d["weight"]))
w_sq=np.arange(d["weight"].min(), d["weight"].max(), 0.2)
to_get=(w_sq-np.mean(w_sq))
data=dict(N=len(weight), W=weight.tolist(), h=d.height.values, GL=len(to_get),␣
↪gen=to_get.tolist())
fit=model_post1.sample(data=data)
az.summary(fit,var_names=['alpha','beta','sigma'],kind='stats')
```

```
INFO:cmdstanpy:start chain 1
INFO:cmdstanpy:start chain 2
INFO:cmdstanpy:start chain 3
INFO:cmdstanpy:start chain 4
INFO:cmdstanpy:finish chain 2
INFO:cmdstanpy:finish chain 4
INFO:cmdstanpy:finish chain 3
INFO:cmdstanpy:finish chain 1
```

[17]:

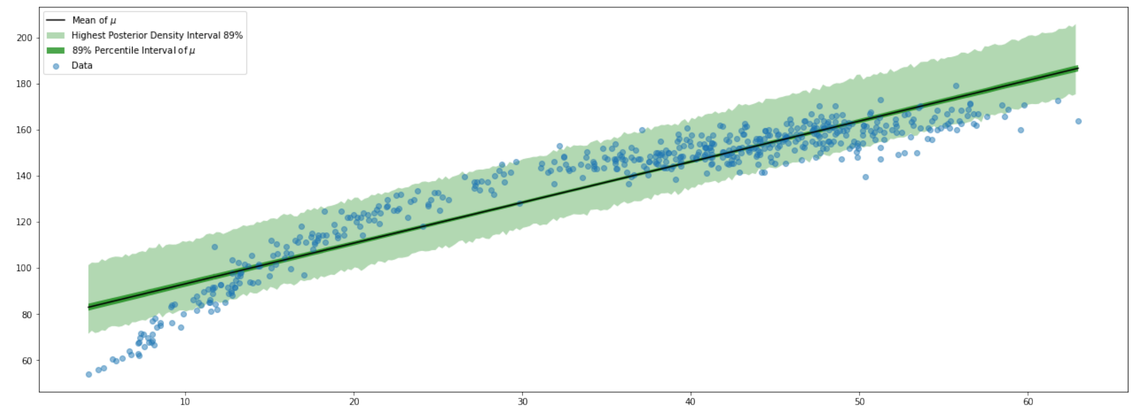
	mean	sd	hdi_3%	hdi_97%
alpha	138.281	0.408	137.518	139.022
beta	1.764	0.028	1.712	1.817
sigma	9.383	0.289	8.860	9.947

[18]:
```
alpha_fit=fit.stan_variable('alpha')
beta_fit=fit.stan_variable('beta')
mu_fit=fit.stan_variable('mu')
h_sim=fit.stan_variable('h_sim')
hdi_height = az.hdi(h_sim, 0.89)
hdi_mu = az.hdi(mu_fit, 0.89)

fig, axes = plt.subplots(figsize=(22, 8))

axes.fill_between(w_sq, hdi_height[:,0], hdi_height[:,1], facecolor='green',␣
↪alpha=0.3);
axes.fill_between(d.weight.values, hdi_mu[:,0], hdi_mu[:,1], facecolor='green',␣
↪alpha=0.7);
axes.scatter(d.weight,d.height,alpha=0.5)
axes.plot(d.weight.values, np.mean(mu_fit,0), color='black')
axes.legend(['Mean of $\mu$', 'Highest Posterior Density Interval 89%', '89%␣
↪Percentile Interval of $\mu$', 'Data'])
plt.show()
```

```
/mnt/c/Users/jkurek1/Desktop/DataAnalytics/venv/lib/python3.6/site-
packages/arviz/stats/stats.py:459: FutureWarning: hdi currently interprets 2d
data as (draw, shape) but this will change in a future release to (chain, draw)
for coherence with other functions
  FutureWarning,
```



To create better fit for our data we'll have to use Polynomial regression. To create polynomial regression we'll have to add powers of our predictor variable into model. First we'll try creating second order regression for our fit. We can describe our model as:

$$height \sim \mathrm{Normal}(\mu, \sigma),$$

$$\mu = \alpha + \beta_1(w - \bar{w}) + \beta_2(w - \bar{w})^2,$$

$$\alpha \sim \mathrm{N}ormal(166, 20)$$

$\beta_1 \sim \mathrm{Log}\text{-}Normal(0, 1)$

$$\beta_2 \sim \mathrm{N}ormal(-0.5, 0.2)$$

$$\sigma \sim \mathrm{U}niform(0, 20)$$

[19]:
```
with open('prio3.stan', 'r') as file:
    print(file.read())
```

```
data {
  int N;
  real W[N];
}

generated quantities {
  real alpha = normal_rng(166,20);
  real beta1 = lognormal_rng(0,1);
  real beta2 = normal_rng(-0.5,0.2);
  real sigma = uniform_rng(0,10);

  real y_sim[N];
  for (k in 1:N) {
    y_sim[k] = normal_rng(beta2 * W[N]^2 + beta1*W[N]+alpha,sigma);
  }
```

```
}
```

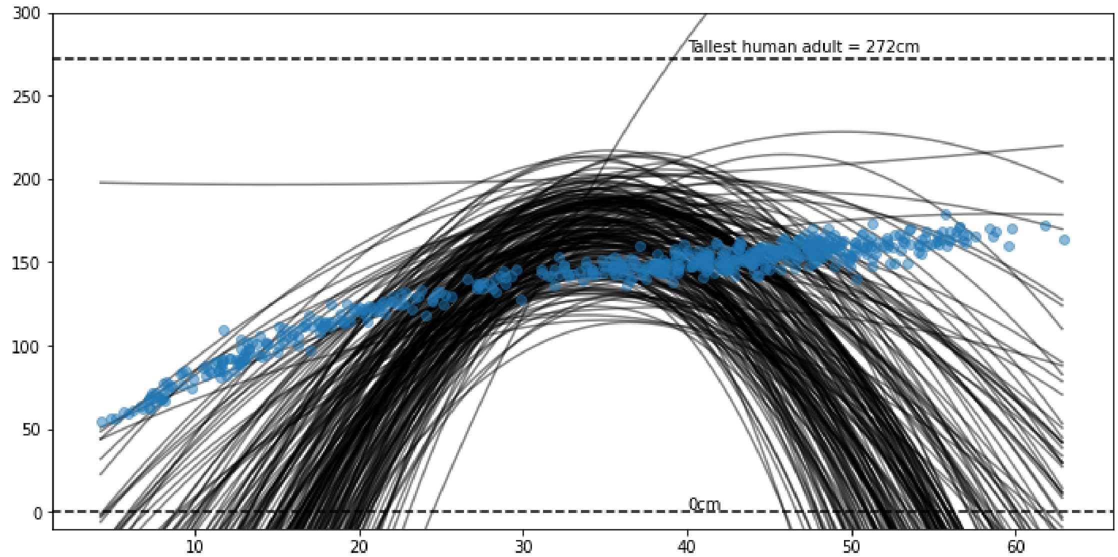
[20]:
```
model_prior_quad=CmdStanModel(stan_file='prio3.stan')
Wn = np.arange(d["weight"].min(), d["weight"].max(), 0.2).tolist()
W = Wn - np.mean(Wn)
data=dict(N=len(W),W=W)
sim=model_prior_quad.sample(data=data,
                     fixed_param=True,
                     iter_warmup=0,
                     chains=1)
alpha_sim=sim.stan_variable('alpha')
beta1_sim=sim.stan_variable('beta1')
beta2_sim=sim.stan_variable('beta2')
y_sim=sim.stan_variable('y_sim')
```

```
INFO:cmdstanpy:compiling stan program, exe file:
/mnt/c/ola/DataAnalytics/lab05/prio3
INFO:cmdstanpy:compiler options: stanc_options=None, cpp_options=None
INFO:cmdstanpy:compiled model file: /mnt/c/ola/DataAnalytics/lab05/prio3
INFO:cmdstanpy:start chain 1
INFO:cmdstanpy:finish chain 1
```

[21]:
```
fig, ax = plt.subplots(figsize=(12, 6))
for i in range(200):
    tepp = alpha_sim[i]+beta1_sim[i]*W + beta2_sim[i]*(W**2)
    ax.plot(Wn,tepp, alpha=0.5,zorder=0,color = 'black')

ax.scatter(d.weight,d.height,alpha = 0.5)
ax.axhline(272, color = 'black', linestyle='--')
ax.text(40,276,'Tallest human adult = 272cm')

ax.axhline(0, color = 'black', linestyle='--')
ax.text(40,2,'0cm')
ax.set_ylim([-10 ,300])
plt.show()
```



[22]:
```
with open('post_quad.stan', 'r') as file:
    print(file.read())
```

```
data {
  int N;
  vector[N] W;
  vector[N] W2;
  real h[N];
  int GL;
  vector[GL] gen;
  vector[GL] gen2;
}

parameters {
  real alpha;
  real beta1;
  real beta2;
  real<lower=0, upper=20> sigma;
}

transformed parameters {
  vector[N] mu;
  for (i in 1:N) {
    mu[i] = alpha + beta1 * (W[i]) + beta2 * (W2[i]);
  }
}

model {
  alpha ~ normal(166,20);
```

```
  beta1 ~ lognormal(0,1);
  beta2 ~ normal(-0.5,0.2);
  sigma ~ uniform(0,20);
  h ~ normal(mu, sigma);
}

generated quantities {
  real h_sim[GL];
  for (i in 1:GL) {
    h_sim[i] = normal_rng(alpha + beta1*(gen[i]) + beta2*(gen2[i]), sigma);
  }
}
```

[23]:
```
model_quad=CmdStanModel(stan_file='post_quad.stan')
```

```
INFO:cmdstanpy:compiling stan program, exe file:
/mnt/c/ola/DataAnalytics/lab05/post_quad
INFO:cmdstanpy:compiler options: stanc_options=None, cpp_options=None
INFO:cmdstanpy:compiled model file: /mnt/c/ola/DataAnalytics/lab05/post_quad
```

[24]:
```
weight = (d["weight"]-np.mean(d["weight"]))
weight2 = weight**2
#w_sq=np.arange(d["weight"].min(), d["weight"].max(), 0.01)
to_get= weight
to_get2 = to_get**2
data=dict(N=len(weight), W=weight.tolist(), W2=weight2.tolist(), h=d.height.
 ↪values, GL=len(to_get), gen=to_get.tolist(), gen2=to_get2.tolist())
fit=model_quad.sample(data=data)
```

```
INFO:cmdstanpy:start chain 1
INFO:cmdstanpy:start chain 2
INFO:cmdstanpy:start chain 3
INFO:cmdstanpy:start chain 4
INFO:cmdstanpy:finish chain 4
INFO:cmdstanpy:finish chain 2
INFO:cmdstanpy:finish chain 1
INFO:cmdstanpy:finish chain 3
```

[25]:
```
az.summary(fit,var_names=['alpha','beta1','beta2','sigma'],kind='stats')
```

[25]:

	mean	sd	hdi_3%	hdi_97%
alpha	146.682	0.376	145.970	147.386
beta1	1.453	0.020	1.415	1.490
beta2	-0.039	0.001	-0.041	-0.036
sigma	5.782	0.175	5.459	6.107

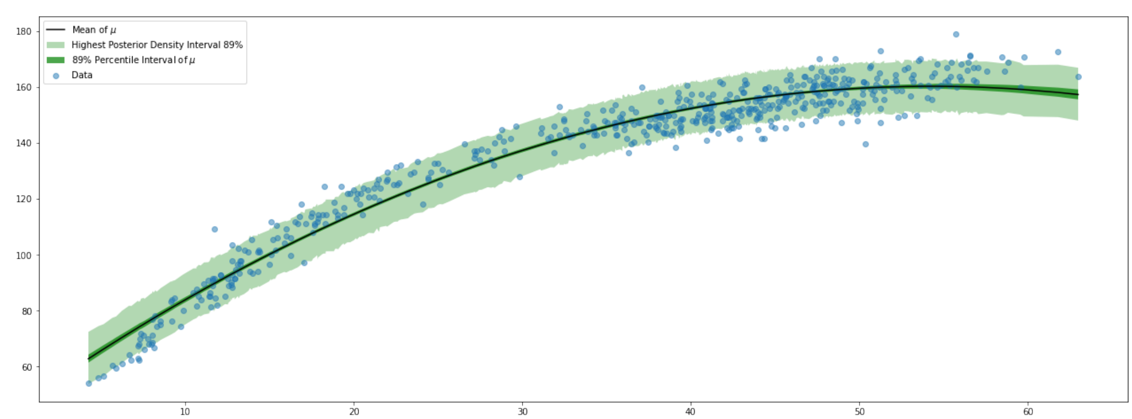
[26]:

```
alpha_fit=fit.stan_variable('alpha')
beta1_fit=fit.stan_variable('beta1')
beta2_fit=fit.stan_variable('beta2')
mu_fit=fit.stan_variable('mu')
h_sim=fit.stan_variable('h_sim')
hdi_height = az.hdi(h_sim, 0.89)
hdi_mu = az.hdi(mu_fit, 0.89)

fig, axes = plt.subplots(figsize=(22, 8))

axes.fill_between(d.weight.values, hdi_height[:,0], hdi_height[:,1],␣
 ↪facecolor='green', alpha=0.3);
axes.fill_between(d.weight.values, hdi_mu[:,0], hdi_mu[:,1], facecolor='green',␣
 ↪alpha=0.7);
axes.scatter(d.weight,d.height,alpha=0.5)
axes.plot(d.weight.values, np.mean(mu_fit,0), color='black')
axes.legend(['Mean of $\mu$', 'Highest Posterior Density Interval 89%', '89%␣
 ↪Percentile Interval of $\mu$', 'Data'])
plt.show()
```

```
/mnt/c/Users/jkurek1/Desktop/DataAnalytics/venv/lib/python3.6/site-
packages/arviz/stats/stats.py:459: FutureWarning: hdi currently interprets 2d
data as (draw, shape) but this will change in a future release to (chain, draw)
for coherence with other functions
  FutureWarning,
```



Regression with 3rd order polynomial:

$$height \sim \text{Normal}(\mu, \sigma),$$

$$\mu = \alpha + \beta_1(w - \bar{w}) + \beta_2(w - \bar{w})^2 + \beta_3(w - \bar{w})^3,$$

$$\alpha \sim \text{Normal}(166, 20)$$

$\beta_1 \sim \text{Log-}Normal(0, 1)$

$$\beta_2 \sim Normal(-0.5, 0.2)$$
$$\beta_3 \sim Normal(0, 1)$$
$$\sigma \sim Uniform(0, 20)$$

[27]:
```python
with open('post_3rd.stan', 'r') as file:
    print(file.read())
```

```
data {
  int N;
  vector[N] W;
  vector[N] W2;
  vector[N] W3;
  real h[N];
  int GL;
  vector[GL] gen;
  vector[GL] gen2;
  vector[GL] gen3;
}

parameters {
  real alpha;
  real beta1;
  real beta2;
  real beta3;
  real<lower=0, upper=20> sigma;
}

transformed parameters {
  vector[N] mu;
  for (i in 1:N) {
    mu[i] = alpha + beta1 * (W[i]) + beta2 * (W2[i]) + beta3 * (W3[i]);
  }
}

model {
  alpha ~ normal(166,20);
  beta1 ~ lognormal(0,1);
  beta2 ~ normal(-0.5,0.2);
  beta3 ~ normal(0,1);
  sigma ~ uniform(0,20);
  h ~ normal(mu, sigma);
}

generated quantities {
  real h_sim[GL];
```

```
  for (i in 1:GL) {
    h_sim[i] = normal_rng(alpha+beta1*(gen[i])+beta2*(gen2[i])+beta3*(gen3[i]),
sigma);
  }
}
```

[28]:
```
model_3rd=CmdStanModel(stan_file='post_3rd.stan')
```

```
INFO:cmdstanpy:compiling stan program, exe file:
/mnt/c/ola/DataAnalytics/lab05/post_3rd
INFO:cmdstanpy:compiler options: stanc_options=None, cpp_options=None
INFO:cmdstanpy:compiled model file: /mnt/c/ola/DataAnalytics/lab05/post_3rd
```

[29]:
```
weight = (d["weight"]-np.mean(d["weight"]))
weight2 = weight**2
weight3 = weight**3
#w_sq=np.arange(d["weight"].min(), d["weight"].max(), 0.01)
to_get= weight
to_get2 = to_get**2
to_get3 = to_get**3
data=dict(N=len(weight), W=weight.tolist(), W2=weight2.tolist(), W3=weight3.
 ↪tolist(), h=d.height.values,
          GL=len(to_get), gen=to_get.tolist(), gen2=to_get2.tolist(),␣
 ↪gen3=to_get3.tolist())
fit=model_3rd.sample(data=data)
```

```
INFO:cmdstanpy:start chain 1
INFO:cmdstanpy:start chain 2
INFO:cmdstanpy:start chain 3
INFO:cmdstanpy:start chain 4
INFO:cmdstanpy:finish chain 2
INFO:cmdstanpy:finish chain 1
INFO:cmdstanpy:finish chain 4
INFO:cmdstanpy:finish chain 3
```

[30]:
```
az.summary(fit,var_names=['alpha','beta1','beta2','sigma'],kind='stats')
```

[30]:

	mean	sd	hdi_3%	hdi_97%
alpha	146.744	0.318	146.160	147.337
beta1	1.021	0.034	0.953	1.083
beta2	-0.030	0.001	-0.033	-0.028
sigma	4.849	0.147	4.568	5.120

[31]:
```
alpha_fit=fit.stan_variable('alpha')
mu_fit=fit.stan_variable('mu')
h_sim=fit.stan_variable('h_sim')
hdi_height = az.hdi(h_sim, 0.89)
```

```
hdi_mu = az.hdi(mu_fit, 0.89)

fig, axes = plt.subplots(figsize=(22, 8))

axes.fill_between(d.weight.values, hdi_height[:,0], hdi_height[:,1],␣
↪facecolor='green', alpha=0.3);
axes.fill_between(d.weight.values, hdi_mu[:,0], hdi_mu[:,1], facecolor='green',␣
↪alpha=0.7);
axes.scatter(d.weight,d.height,alpha=0.5)
axes.plot(d.weight.values, np.mean(mu_fit,0), color='black')
axes.legend(['Mean of $\mu$', 'Highest Posterior Density Interval 89%', '89%␣
↪Percentile Interval of $\mu$', 'Data'])
plt.show()
```

```
/mnt/c/Users/jkurek1/Desktop/DataAnalytics/venv/lib/python3.6/site-
packages/arviz/stats/stats.py:459: FutureWarning: hdi currently interprets 2d
data as (draw, shape) but this will change in a future release to (chain, draw)
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```