

BDA - Project

Anonymous

Contents

Decision Analysis for Factory Data

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This submission is completed in python with pystan.

```
import numpy as np
import matplotlib.pyplot as plt
# with out this, plots from matplotlib won't knit on windows
import matplotlib
matplotlib.use('TkAgg')
import pystan
import arviz as az
from pathlib import Path
from matplotlib.patches import Patch
from matplotlib.lines import Line2D

fig_size=(12,6)# parameters for figures throughout this assignment
num_bins = 20 #
font_size=15

import pystan
print("pystan version:", pystan.__version__)

## pystan version: 2.19.0.0

model_path = 'stan_models'
data_file = 'data/data.txt'
accident_data = np.loadtxt(data_file)
print(accident_data.shape)

## (6, 15)

mean_value = np.mean(accident_data) # mean value approximately 25 cases per 10,000 people
# it's very un likely to change 50% of the mean, so 2.57*sigma = mean_value/2
sigma = mean_value / (2*2.57)
sigma

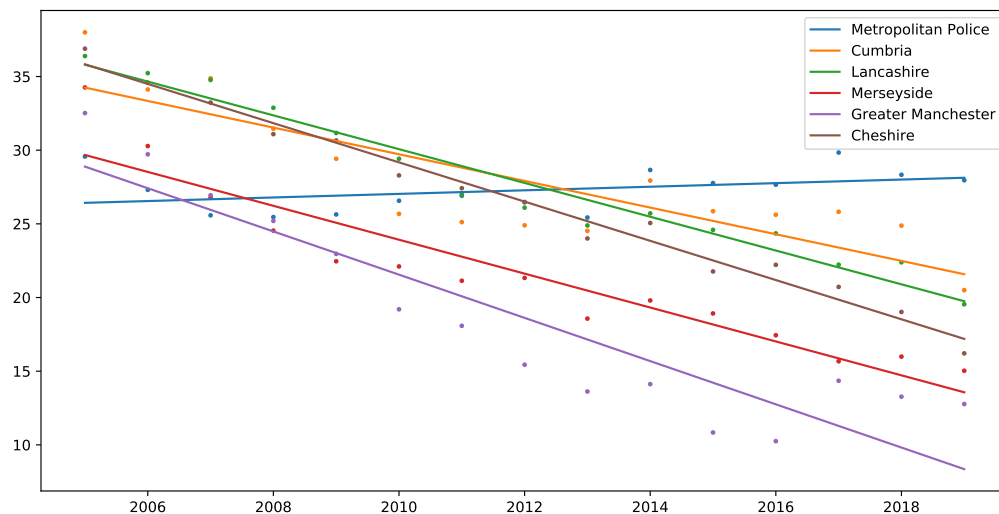
## 4.854734111543451

area_names = ["Metropolitan Police", 'Cumbria','Lancashire',
              'Merseyside','Greater Manchester','Cheshire']
```

```
plt.figure(figsize=(12, 6));
years = np.arange(2005, 2020, 1).astype(np.int)
print(years.shape)
```

```
## (15,)
```

```
for i in range(6):
    plt.scatter(years, accident_data[i, :], marker='.', s=20)
    fit = np.polyfit(years, accident_data[i, :], 1)
    fitted_values = np.polyval(fit, years)
    plt.plot(years, fitted_values, label=area_names[i])
plt.legend()
plt.show()
```



3.3 Hierarchical Model

```
model_name = 'accident_hierarchical.stan'
stan_model = pystan.StanModel(file=model_path + '/' + model_name)
```

```
## INFO:pystan:COMPILING THE C++ CODE FOR MODEL anon_model_9fb09f0a30d029d43ce52bd2384506d8 NOW.
print(stan_model.model_code)
```

```
## //
## // This Stan program defines a simple model, with a
## // vector of values 'y' modeled as normally distributed
## // with mean 'mu' and standard deviation 'sigma'.
## //
## // Learn more about model development with Stan at:
## //
## //   http://mc-stan.org/users/interfaces/rstan.html
## //   https://github.com/stan-dev/rstan/wiki/RStan-Getting-Started
## //
```

```

## data {
##   int<lower=0> N; // the number of police force
##   int<lower=0> Y; // the number of years has been studied, year 2005 corresponds to 1
##   matrix[N,Y] accidentData;//accident data
##   int prior_choice; // choose different setup for prior distribution
##   int xpred; // year of prediction (actual year)
## }
##
##
## parameters {
##   real mu_alpha;
##   real mu_beta;
##   real<lower=0> sigma_alpha;
##   real<lower=0> sigma_beta;
##   vector[N] alpha;
##   vector[N] beta;
##   vector<lower=0>[N] sigma;
## }
##
##
## transformed parameters{
##   matrix[N,Y]mu;
##   for(i in 1:N)
##     for(j in 1:Y)
##       mu[i,j]=alpha[i]+beta[i]*j;
## }
##
##
## model {
##   if (prior_choice==3){
##     // bigger variance
##     mu_alpha~normal(30,40);
##     mu_beta~normal(0,10);
##     sigma_alpha~normal(10,10);
##     sigma_beta~normal(3,6);
##   } else if (prior_choice==2){
##     // uniform prior
##   } else {
##     // default choice with moderate variance
##     mu_alpha~normal(30,20);
##     mu_beta~normal(0,4.85);
##     sigma_alpha~normal(10,5);
##     sigma_beta~normal(3,3);
##   }
##
##   //for each police force
##   for(i in 1:N){
##     alpha[i]~normal(mu_alpha,sigma_alpha);
##     beta[i]~normal(mu_beta,sigma_beta);
##   }
##
##   //for each police force
##   for(i in 1:N){
##     //for each observed year

```

```

##     for(j in 1:Y){
##         accidentData[i,j]~normal(mu[i,j],sigma[i]);
##     }
## }
##
##
## generated quantities{
##     //log likelihood
##     matrix[N,Y] log_lik;
##     matrix[N,Y] yrep;
##     //accident prediction in 2020 in different police force
##     vector[N] pred;
##
##     //for each police force
##     for(i in 1:N){
##         // 2005 -> 1, 2006 -> 2, ..., 2020 -> 16
##         pred[i]=normal_rng(alpha[i]+beta[i]*(xpred-2004),sigma[i]);
##     }
##
##     for(i in 1:N){
##         for(j in 1:Y){
##             // do posterior sampling and try to reproduce the original data
##             yrep[i,j]=normal_rng(mu[i,j],sigma[i]);
##             // prepare log likelihood for PSIS-L00
##             log_lik[i,j]=normal_lpdf(accidentData[i,j]|mu[i,j],sigma[i]);
##         }
##     }
## }
## }

data_for_stan = dict(
    N = accident_data.shape[0],
    Y = accident_data.shape[1],
    accidentData = accident_data,
    years = np.arange(1, accident_data.shape[1]+1), # stan index starts from 1
    xpred=2020,
    prior_choice=1
)
stan_results = stan_model.sampling(data=data_for_stan)
print(stan_results)

## Inference for Stan model: anon_model_9fb09f0a30d029d43ce52bd2384506d8.
## 4 chains, each with iter=2000; warmup=1000; thin=1;
## post-warmup draws per chain=1000, total post-warmup draws=4000.
##
##          mean se_mean      sd  2.5%   25%   50%   75%  97.5%  n_eff  Rhat
## mu_alpha    32.68    0.06   2.79  27.02  31.13  32.7  34.31  38.18  2423   1.0
## mu_beta     -0.97   8.3e-3   0.37  -1.71  -1.17  -0.97  -0.77  -0.19  2013   1.0
## sigma_alpha   6.39    0.04   2.54   2.92   4.51   5.86   7.78  12.67  3234   1.0
## sigma_beta    0.82    0.01   0.42   0.38   0.56   0.71   0.95   1.88  1653   1.0
## alpha[1]     26.64    0.02   0.88  24.93  26.08  26.62  27.19  28.43  2631   1.0
## alpha[2]     34.92    0.03    1.5  31.92  33.98  34.95  35.86  37.8   2049   1.0
## alpha[3]     36.85    0.01   0.69  35.48  36.39  36.87  37.3   38.17  2411   1.0
## alpha[4]     30.87    0.03   1.16  28.64  30.14  30.86  31.58  33.2   2124   1.0

```

## alpha[5]	30.28	0.04	1.7	26.86	29.19	30.3	31.38	33.6	2219	1.0
## alpha[6]	37.1	0.01	0.51	36.08	36.78	37.11	37.44	38.1	2274	1.0
## beta[1]	0.08	2.0e-3	0.1	-0.12	0.02	0.08	0.15	0.27	2545	1.0
## beta[2]	-0.88	3.6e-3	0.17	-1.2	-0.99	-0.89	-0.78	-0.55	2154	1.0
## beta[3]	-1.14	1.5e-3	0.08	-1.28	-1.19	-1.14	-1.09	-0.99	2454	1.0
## beta[4]	-1.15	2.7e-3	0.13	-1.41	-1.23	-1.15	-1.07	-0.9	2240	1.0
## beta[5]	-1.45	4.0e-3	0.19	-1.81	-1.58	-1.45	-1.33	-1.07	2279	1.0
## beta[6]	-1.32	1.2e-3	0.06	-1.44	-1.36	-1.33	-1.29	-1.21	2123	1.0
## sigma[1]	1.56	7.1e-3	0.36	1.05	1.31	1.5	1.75	2.47	2675	1.0
## sigma[2]	2.86	0.01	0.65	1.92	2.39	2.75	3.21	4.44	3596	1.0
## sigma[3]	1.25	4.9e-3	0.28	0.84	1.05	1.21	1.39	1.91	3244	1.0
## sigma[4]	2.15	9.4e-3	0.5	1.44	1.8	2.06	2.4	3.37	2808	1.0
## sigma[5]	3.26	0.01	0.72	2.18	2.75	3.16	3.64	4.97	3223	1.0
## sigma[6]	0.93	4.0e-3	0.22	0.63	0.78	0.9	1.04	1.45	2855	1.0
## mu[1,1]	26.73	0.02	0.79	25.18	26.21	26.7	27.22	28.35	2674	1.0
## mu[2,1]	34.04	0.03	1.36	31.31	33.19	34.07	34.89	36.65	2080	1.0
## mu[3,1]	35.72	0.01	0.62	34.47	35.3	35.73	36.12	36.92	2436	1.0
## mu[4,1]	29.72	0.02	1.05	27.71	29.05	29.71	30.37	31.83	2150	1.0
## mu[5,1]	28.83	0.03	1.54	25.74	27.84	28.83	29.82	31.82	2249	1.0
## mu[6,1]	35.77	9.6e-3	0.46	34.84	35.49	35.78	36.08	36.68	2320	1.0
## mu[1,2]	26.81	0.01	0.71	25.44	26.35	26.79	27.25	28.26	2737	1.0
## mu[2,2]	33.15	0.03	1.22	30.65	32.4	33.17	33.93	35.54	2131	1.0
## mu[3,2]	34.58	0.01	0.56	33.46	34.21	34.59	34.95	35.67	2475	1.0
## mu[4,2]	28.56	0.02	0.94	26.79	27.97	28.56	29.14	30.45	2186	1.0
## mu[5,2]	27.38	0.03	1.38	24.63	26.48	27.38	28.27	30.07	2298	1.0
## mu[6,2]	34.45	8.6e-3	0.42	33.6	34.19	34.46	34.73	35.26	2388	1.0
## mu[1,3]	26.89	0.01	0.63	25.68	26.49	26.88	27.28	28.22	2832	1.0
## mu[2,3]	32.27	0.02	1.1	30.02	31.6	32.28	32.97	34.42	2215	1.0
## mu[3,3]	33.44	9.9e-3	0.5	32.44	33.11	33.45	33.77	34.41	2537	1.0
## mu[4,3]	27.41	0.02	0.84	25.84	26.88	27.4	27.94	29.09	2252	1.0
## mu[5,3]	25.93	0.03	1.24	23.48	25.13	25.93	26.72	28.36	2379	1.0
## mu[6,3]	33.13	7.5e-3	0.37	32.36	32.89	33.13	33.38	33.84	2490	1.0
## mu[1,4]	26.97	0.01	0.56	25.93	26.61	26.96	27.32	28.12	2975	1.0
## mu[2,4]	31.39	0.02	0.98	29.35	30.77	31.4	32.02	33.32	2354	1.0
## mu[3,4]	32.31	8.7e-3	0.45	31.43	32.01	32.31	32.6	33.19	2636	1.0
## mu[4,4]	26.26	0.02	0.75	24.83	25.8	26.25	26.73	27.76	2377	1.0
## mu[5,4]	24.47	0.02	1.11	22.28	23.75	24.49	25.19	26.69	2511	1.0
## mu[6,4]	31.8	6.5e-3	0.33	31.11	31.59	31.81	32.02	32.44	2649	1.0
## mu[1,5]	27.06	8.9e-3	0.5	26.12	26.73	27.05	27.37	28.08	3157	1.0
## mu[2,5]	30.5	0.02	0.89	28.65	29.94	30.52	31.09	32.23	2586	1.0
## mu[3,5]	31.17	7.5e-3	0.4	30.38	30.91	31.17	31.42	31.97	2795	1.0
## mu[4,5]	25.11	0.01	0.67	23.82	24.69	25.1	25.53	26.43	2608	1.0
## mu[5,5]	23.02	0.02	1.0	21.04	22.36	23.03	23.67	25.03	2724	1.0
## mu[6,5]	30.48	5.5e-3	0.3	29.87	30.29	30.48	30.67	31.05	2883	1.0
## mu[1,6]	27.14	7.7e-3	0.45	26.29	26.85	27.13	27.42	28.05	3419	1.0
## mu[2,6]	29.62	0.01	0.81	27.92	29.12	29.63	30.15	31.2	2965	1.0
## mu[3,6]	30.03	6.5e-3	0.36	29.31	29.8	30.03	30.26	30.74	3041	1.0
## mu[4,6]	23.95	0.01	0.6	22.76	23.58	23.95	24.34	25.15	3029	1.0
## mu[5,6]	21.57	0.02	0.92	19.76	20.96	21.58	22.16	23.41	3045	1.0
## mu[6,6]	29.15	4.8e-3	0.27	28.59	28.98	29.15	29.32	29.68	3176	1.0
## mu[1,7]	27.22	6.7e-3	0.42	26.43	26.95	27.22	27.48	28.06	3833	1.0
## mu[2,7]	28.73	0.01	0.77	27.15	28.26	28.75	29.23	30.22	3532	1.0
## mu[3,7]	28.89	5.7e-3	0.33	28.24	28.68	28.89	29.1	29.56	3383	1.0
## mu[4,7]	22.8	9.1e-3	0.56	21.7	22.45	22.8	23.16	23.92	3766	1.0

## mu[5,7]	20.12	0.01	0.87	18.37	19.57	20.11	20.67	21.88	3581	1.0
## mu[6,7]	27.83	4.2e-3	0.25	27.32	27.67	27.83	27.99	28.32	3570	1.0
## mu[1,8]	27.3	6.3e-3	0.41	26.52	27.04	27.3	27.56	28.11	4122	1.0
## mu[2,8]	27.85	0.01	0.76	26.3	27.37	27.86	28.34	29.31	4046	1.0
## mu[3,8]	27.76	5.3e-3	0.32	27.12	27.55	27.75	27.96	28.41	3747	1.0
## mu[4,8]	21.65	8.0e-3	0.54	20.57	21.3	21.66	22.0	22.73	4594	1.0
## mu[5,8]	18.67	0.01	0.86	16.94	18.14	18.65	19.21	20.42	4278	1.0
## mu[6,8]	26.5	3.9e-3	0.24	26.03	26.35	26.5	26.66	26.98	3966	1.0
## mu[1,9]	27.38	6.6e-3	0.42	26.58	27.11	27.39	27.65	28.22	4074	1.0
## mu[2,9]	26.97	0.01	0.78	25.42	26.47	26.98	27.48	28.48	4344	1.0
## mu[3,9]	26.62	5.2e-3	0.33	25.96	26.41	26.61	26.83	27.29	3961	1.0
## mu[4,9]	20.5	7.9e-3	0.56	19.39	20.14	20.5	20.85	21.63	4977	1.0
## mu[5,9]	17.22	0.01	0.89	15.46	16.67	17.2	17.77	19.04	4543	1.0
## mu[6,9]	25.18	3.9e-3	0.25	24.68	25.02	25.18	25.34	25.68	4155	1.0
## mu[1,10]	27.47	7.4e-3	0.46	26.58	27.18	27.47	27.76	28.37	3855	1.0
## mu[2,10]	26.08	0.01	0.84	24.41	25.55	26.09	26.63	27.74	4303	1.0
## mu[3,10]	25.48	5.6e-3	0.35	24.78	25.26	25.48	25.7	26.19	3925	1.0
## mu[4,10]	19.34	8.7e-3	0.6	18.15	18.96	19.34	19.72	20.57	4770	1.0
## mu[5,10]	15.77	0.01	0.96	13.82	15.17	15.76	16.36	17.7	4343	1.0
## mu[6,10]	23.85	4.2e-3	0.27	23.32	23.69	23.85	24.03	24.4	4055	1.0
## mu[1,11]	27.55	8.5e-3	0.51	26.55	27.23	27.55	27.87	28.56	3628	1.0
## mu[2,11]	25.2	0.01	0.92	23.36	24.61	25.21	25.79	27.02	4047	1.0
## mu[3,11]	24.35	6.4e-3	0.39	23.59	24.09	24.34	24.59	25.13	3734	1.0
## mu[4,11]	18.19	0.01	0.67	16.84	17.76	18.18	18.61	19.54	4388	1.0
## mu[5,11]	14.32	0.02	1.06	12.19	13.66	14.31	14.99	16.43	4033	1.0
## mu[6,11]	22.53	4.9e-3	0.3	21.93	22.34	22.53	22.72	23.13	3632	1.0
## mu[1,12]	27.63	9.8e-3	0.57	26.48	27.27	27.63	28.0	28.76	3424	1.0
## mu[2,12]	24.32	0.02	1.03	22.2	23.67	24.32	24.97	26.39	3750	1.0
## mu[3,12]	23.21	7.4e-3	0.44	22.37	22.92	23.19	23.49	24.08	3513	1.0
## mu[4,12]	17.04	0.01	0.75	15.54	16.57	17.01	17.52	18.53	3995	1.0
## mu[5,12]	12.87	0.02	1.18	10.49	12.13	12.86	13.61	15.25	3715	1.0
## mu[6,12]	21.21	5.9e-3	0.33	20.53	21.0	21.2	21.42	21.87	3175	1.0
## mu[1,13]	27.71	0.01	0.65	26.39	27.31	27.72	28.13	28.98	3255	1.0
## mu[2,13]	23.43	0.02	1.15	21.08	22.7	23.42	24.17	25.74	3491	1.0
## mu[3,13]	22.07	8.5e-3	0.49	21.13	21.74	22.06	22.39	23.04	3322	1.0
## mu[4,13]	15.89	0.01	0.84	14.24	15.35	15.86	16.42	17.56	3619	1.0
## mu[5,13]	11.42	0.02	1.32	8.8	10.59	11.41	12.26	14.07	3450	1.0
## mu[6,13]	19.88	6.9e-3	0.37	19.13	19.65	19.88	20.13	20.62	2889	1.0
## mu[1,14]	27.8	0.01	0.73	26.33	27.34	27.8	28.26	29.2	3114	1.0
## mu[2,14]	22.55	0.02	1.28	19.94	21.75	22.53	23.36	25.15	3286	1.0
## mu[3,14]	20.93	9.8e-3	0.55	19.88	20.57	20.93	21.29	22.03	3171	1.0
## mu[4,14]	14.73	0.02	0.95	12.89	14.13	14.72	15.33	16.63	3347	1.0
## mu[5,14]	9.97	0.03	1.47	7.07	9.02	9.98	10.91	12.89	3244	1.0
## mu[6,14]	18.56	8.0e-3	0.42	17.72	18.29	18.54	18.83	19.4	2723	1.0
## mu[1,15]	27.88	0.01	0.81	26.23	27.37	27.89	28.4	29.46	3011	1.0
## mu[2,15]	21.66	0.03	1.41	18.8	20.77	21.64	22.56	24.52	3128	1.0
## mu[3,15]	19.8	0.01	0.61	18.6	19.39	19.79	20.19	21.03	3055	1.0
## mu[4,15]	13.58	0.02	1.05	11.55	12.91	13.57	14.24	15.67	3150	1.0
## mu[5,15]	8.51	0.03	1.62	5.35	7.46	8.52	9.56	11.72	3087	1.0
## mu[6,15]	17.23	9.1e-3	0.46	16.31	16.93	17.22	17.53	18.18	2605	1.0
## log_lik[1,1]	-3.43	0.02	1.26	-6.57	-4.09	-3.18	-2.49	-1.77	3315	1.0
## log_lik[2,1]	-3.12	0.01	0.71	-4.84	-3.52	-3.0	-2.61	-2.11	2827	1.0
## log_lik[3,1]	-1.39	7.1e-3	0.35	-2.24	-1.58	-1.34	-1.15	-0.86	2475	1.0
## log_lik[4,1]	-4.34	0.02	1.39	-7.65	-5.12	-4.11	-3.3	-2.35	3756	1.0

## log_lik[5,1]	-2.91	0.01	0.6	-4.41	-3.22	-2.79	-2.49	-2.08	2779	1.0
## log_lik[6,1]	-1.75	0.01	0.66	-3.37	-2.09	-1.61	-1.27	-0.85	3142	1.0
## log_lik[1,2]	-1.51	5.4e-3	0.28	-2.15	-1.66	-1.48	-1.32	-1.06	2643	1.0
## log_lik[2,2]	-2.09	5.5e-3	0.27	-2.71	-2.25	-2.07	-1.9	-1.64	2474	1.0
## log_lik[3,2]	-1.36	6.2e-3	0.31	-2.09	-1.54	-1.32	-1.14	-0.86	2540	1.0
## log_lik[4,2]	-2.12	7.2e-3	0.39	-3.06	-2.32	-2.05	-1.84	-1.54	2888	1.0
## log_lik[5,2]	-2.46	7.3e-3	0.36	-3.35	-2.64	-2.4	-2.21	-1.91	2508	1.0
## log_lik[6,2]	-0.93	5.8e-3	0.26	-1.52	-1.08	-0.9	-0.75	-0.51	2004	1.0
## log_lik[1,3]	-1.81	7.2e-3	0.39	-2.72	-2.01	-1.75	-1.53	-1.21	2885	1.0
## log_lik[2,3]	-2.48	7.4e-3	0.38	-3.38	-2.69	-2.43	-2.21	-1.89	2544	1.0
## log_lik[3,3]	-1.83	8.1e-3	0.45	-2.85	-2.09	-1.75	-1.5	-1.16	3104	1.0
## log_lik[4,3]	-1.78	5.2e-3	0.26	-2.35	-1.93	-1.75	-1.6	-1.35	2476	1.0
## log_lik[5,3]	-2.2	5.0e-3	0.25	-2.74	-2.34	-2.18	-2.03	-1.78	2450	1.0
## log_lik[6,3]	-0.91	5.3e-3	0.24	-1.46	-1.06	-0.88	-0.74	-0.5	2153	1.0
## log_lik[1,4]	-1.92	6.7e-3	0.38	-2.82	-2.13	-1.87	-1.66	-1.33	3251	1.0
## log_lik[2,4]	-2.0	4.2e-3	0.23	-2.49	-2.15	-1.99	-1.84	-1.6	3052	1.0
## log_lik[3,4]	-1.29	4.8e-3	0.25	-1.85	-1.45	-1.28	-1.12	-0.86	2734	1.0
## log_lik[4,4]	-2.08	5.8e-3	0.32	-2.81	-2.26	-2.05	-1.86	-1.59	3020	1.0
## log_lik[5,4]	-2.16	4.4e-3	0.23	-2.65	-2.3	-2.15	-2.0	-1.75	2635	1.0
## log_lik[6,4]	-1.23	5.5e-3	0.31	-1.95	-1.41	-1.19	-1.01	-0.72	3303	1.0
## log_lik[1,5]	-1.85	5.7e-3	0.32	-2.6	-2.03	-1.81	-1.62	-1.32	3173	1.0
## log_lik[2,5]	-2.08	4.0e-3	0.22	-2.56	-2.22	-2.06	-1.92	-1.68	3126	1.0
## log_lik[3,5]	-1.16	4.0e-3	0.22	-1.65	-1.3	-1.15	-1.01	-0.77	3049	1.0
## log_lik[4,5]	-2.57	7.1e-3	0.44	-3.59	-2.8	-2.5	-2.27	-1.93	3825	1.0
## log_lik[5,5]	-2.12	4.1e-3	0.22	-2.58	-2.26	-2.12	-1.97	-1.73	2767	1.0
## log_lik[6,5]	-0.89	4.7e-3	0.23	-1.4	-1.04	-0.88	-0.73	-0.5	2430	1.0
## log_lik[1,6]	-1.45	4.6e-3	0.23	-1.96	-1.59	-1.43	-1.29	-1.05	2576	1.0
## log_lik[2,6]	-3.08	8.2e-3	0.5	-4.3	-3.35	-3.0	-2.72	-2.37	3708	1.0
## log_lik[3,6]	-1.29	4.0e-3	0.22	-1.78	-1.43	-1.28	-1.14	-0.91	3003	1.0
## log_lik[4,6]	-2.12	4.6e-3	0.27	-2.71	-2.28	-2.09	-1.93	-1.68	3453	1.0
## log_lik[5,6]	-2.42	4.4e-3	0.24	-2.96	-2.56	-2.4	-2.25	-2.01	3018	1.0
## log_lik[6,6]	-1.36	5.0e-3	0.3	-2.03	-1.53	-1.33	-1.15	-0.88	3510	1.0
## log_lik[1,7]	-1.4	4.3e-3	0.22	-1.89	-1.53	-1.38	-1.24	-1.01	2681	1.0
## log_lik[2,7]	-2.9	6.7e-3	0.41	-3.89	-3.12	-2.84	-2.61	-2.3	3801	1.0
## log_lik[3,7]	-2.48	8.9e-3	0.56	-3.83	-2.78	-2.38	-2.08	-1.68	3950	1.0
## log_lik[4,7]	-2.03	4.0e-3	0.24	-2.54	-2.18	-2.02	-1.87	-1.64	3506	1.0
## log_lik[5,7]	-2.34	4.0e-3	0.22	-2.82	-2.48	-2.32	-2.18	-1.96	3071	1.0
## log_lik[6,7]	-0.97	3.9e-3	0.21	-1.42	-1.1	-0.96	-0.82	-0.59	2993	1.0
## log_lik[1,8]	-1.53	4.2e-3	0.22	-2.01	-1.67	-1.52	-1.38	-1.14	2773	1.0
## log_lik[2,8]	-2.59	5.0e-3	0.3	-3.29	-2.76	-2.55	-2.38	-2.11	3691	1.0
## log_lik[3,8]	-2.15	6.8e-3	0.43	-3.18	-2.38	-2.08	-1.85	-1.52	4004	1.0
## log_lik[4,8]	-1.7	4.1e-3	0.22	-2.17	-1.84	-1.69	-1.55	-1.32	2939	1.0
## log_lik[5,8]	-2.67	4.6e-3	0.29	-3.33	-2.83	-2.63	-2.47	-2.21	3868	1.0
## log_lik[6,8]	-0.86	4.3e-3	0.22	-1.33	-0.99	-0.84	-0.7	-0.48	2702	1.0
## log_lik[1,9]	-2.28	6.8e-3	0.41	-3.24	-2.49	-2.21	-1.99	-1.68	3542	1.0
## log_lik[2,9]	-2.4	4.4e-3	0.26	-2.97	-2.56	-2.38	-2.22	-1.97	3480	1.0
## log_lik[3,9]	-2.24	7.2e-3	0.46	-3.36	-2.49	-2.17	-1.91	-1.56	4201	1.0
## log_lik[4,9]	-2.15	4.1e-3	0.26	-2.74	-2.3	-2.13	-1.97	-1.73	4105	1.0
## log_lik[5,9]	-2.81	5.3e-3	0.34	-3.59	-2.98	-2.75	-2.58	-2.28	4051	1.0
## log_lik[6,9]	-1.76	6.5e-3	0.4	-2.75	-1.98	-1.7	-1.48	-1.16	3816	1.0
## log_lik[1,10]	-1.71	4.7e-3	0.26	-2.26	-1.87	-1.69	-1.53	-1.26	3050	1.0
## log_lik[2,10]	-2.23	4.3e-3	0.24	-2.75	-2.38	-2.2	-2.06	-1.81	3243	1.0
## log_lik[3,10]	-1.17	3.8e-3	0.21	-1.64	-1.31	-1.17	-1.02	-0.79	3262	1.0
## log_lik[4,10]	-1.72	4.2e-3	0.22	-2.19	-1.86	-1.71	-1.57	-1.34	2752	1.0

## log_lik[5,10]	-2.26	4.1e-3	0.23	-2.78	-2.4	-2.25	-2.1	-1.87	3045	1.0
## log_lik[6,10]	-1.82	7.0e-3	0.44	-2.87	-2.06	-1.75	-1.51	-1.16	4011	1.0
## log_lik[1,11]	-1.4	4.7e-3	0.23	-1.91	-1.55	-1.38	-1.23	-1.0	2422	1.0
## log_lik[2,11]	-2.03	4.2e-3	0.23	-2.52	-2.17	-2.01	-1.86	-1.63	2996	1.0
## log_lik[3,11]	-1.19	3.9e-3	0.22	-1.65	-1.33	-1.18	-1.03	-0.8	3212	1.0
## log_lik[4,11]	-1.77	4.4e-3	0.23	-2.27	-1.92	-1.76	-1.61	-1.37	2699	1.0
## log_lik[5,11]	-2.77	6.2e-3	0.38	-3.67	-2.98	-2.71	-2.51	-2.19	3716	1.0
## log_lik[6,11]	-1.25	5.4e-3	0.29	-1.91	-1.42	-1.22	-1.05	-0.77	2854	1.0
## log_lik[1,12]	-1.4	4.8e-3	0.24	-1.92	-1.55	-1.38	-1.23	-0.99	2458	1.0
## log_lik[2,12]	-2.13	4.6e-3	0.26	-2.72	-2.28	-2.1	-1.95	-1.69	3032	1.0
## log_lik[3,12]	-1.66	5.8e-3	0.35	-2.49	-1.85	-1.61	-1.41	-1.11	3662	1.0
## log_lik[4,12]	-1.74	4.7e-3	0.23	-2.25	-1.88	-1.72	-1.57	-1.33	2524	1.0
## log_lik[5,12]	-2.5	5.8e-3	0.33	-3.27	-2.68	-2.46	-2.28	-1.99	3194	1.0
## log_lik[6,12]	-1.57	7.1e-3	0.43	-2.59	-1.8	-1.5	-1.26	-0.95	3661	1.0
## log_lik[1,13]	-2.46	9.7e-3	0.61	-3.9	-2.82	-2.37	-2.01	-1.55	3968	1.0
## log_lik[2,13]	-2.43	6.5e-3	0.38	-3.35	-2.62	-2.37	-2.17	-1.86	3384	1.0
## log_lik[3,13]	-1.2	4.3e-3	0.23	-1.72	-1.34	-1.19	-1.04	-0.79	2997	1.0
## log_lik[4,13]	-1.74	5.0e-3	0.24	-2.27	-1.89	-1.71	-1.57	-1.33	2370	1.0
## log_lik[5,13]	-2.62	7.1e-3	0.41	-3.65	-2.82	-2.55	-2.34	-2.03	3272	1.0
## log_lik[6,13]	-1.37	6.9e-3	0.4	-2.34	-1.57	-1.31	-1.09	-0.79	3346	1.0
## log_lik[1,14]	-1.5	6.2e-3	0.3	-2.19	-1.67	-1.47	-1.29	-1.03	2264	1.0
## log_lik[2,14]	-2.43	7.2e-3	0.42	-3.47	-2.63	-2.36	-2.14	-1.83	3297	1.0
## log_lik[3,14]	-2.0	9.5e-3	0.58	-3.43	-2.31	-1.89	-1.58	-1.18	3711	1.0
## log_lik[4,14]	-1.95	6.3e-3	0.33	-2.72	-2.13	-1.91	-1.72	-1.43	2719	1.0
## log_lik[5,14]	-2.77	8.8e-3	0.51	-4.08	-3.02	-2.66	-2.41	-2.07	3355	1.0
## log_lik[6,14]	-1.06	6.0e-3	0.31	-1.8	-1.23	-1.02	-0.85	-0.58	2697	1.0
## log_lik[1,15]	-1.47	6.0e-3	0.29	-2.12	-1.62	-1.44	-1.27	-1.01	2224	1.0
## log_lik[2,15]	-2.15	6.2e-3	0.32	-2.94	-2.33	-2.11	-1.93	-1.66	2666	1.0
## log_lik[3,15]	-1.25	5.7e-3	0.28	-1.9	-1.41	-1.23	-1.06	-0.8	2477	1.0
## log_lik[4,15]	-2.04	7.5e-3	0.4	-3.02	-2.23	-1.97	-1.77	-1.45	2790	1.0
## log_lik[5,15]	-3.18	0.01	0.74	-5.05	-3.56	-3.02	-2.64	-2.2	3528	1.0
## log_lik[6,15]	-1.62	0.01	0.59	-3.08	-1.96	-1.5	-1.2	-0.81	3131	1.0
## yrep[1,1]	26.7	0.03	1.77	23.2	25.59	26.67	27.82	30.36	3725	1.0
## yrep[2,1]	34.1	0.05	3.25	27.72	32.07	34.07	36.27	40.52	3638	1.0
## yrep[3,1]	35.7	0.02	1.44	32.84	34.78	35.68	36.6	38.59	3536	1.0
## yrep[4,1]	29.78	0.04	2.46	24.79	28.27	29.76	31.33	34.84	3398	1.0
## yrep[5,1]	28.89	0.07	3.62	21.91	26.6	28.85	31.13	36.28	3057	1.0
## yrep[6,1]	35.76	0.02	1.05	33.61	35.11	35.77	36.43	37.85	3134	1.0
## yrep[1,2]	26.83	0.03	1.7	23.48	25.73	26.8	27.88	30.3	3735	1.0
## yrep[2,2]	33.13	0.05	3.2	26.76	31.11	33.13	35.18	39.52	3532	1.0
## yrep[3,2]	34.57	0.02	1.4	31.68	33.67	34.61	35.49	37.25	3779	1.0
## yrep[4,2]	28.66	0.04	2.4	23.86	27.12	28.66	30.2	33.5	3572	1.0
## yrep[5,2]	27.4	0.06	3.55	20.28	25.11	27.43	29.64	34.51	3642	1.0
## yrep[6,2]	34.48	0.02	1.04	32.34	33.84	34.49	35.13	36.58	3598	1.0
## yrep[1,3]	26.91	0.03	1.74	23.59	25.76	26.89	27.99	30.43	3455	1.0
## yrep[2,3]	32.28	0.05	3.07	26.12	30.38	32.33	34.27	38.26	3658	1.0
## yrep[3,3]	33.43	0.02	1.39	30.73	32.53	33.42	34.3	36.18	3860	1.0
## yrep[4,3]	27.4	0.04	2.36	22.59	25.98	27.39	28.85	32.11	3744	1.0
## yrep[5,3]	25.91	0.06	3.58	18.72	23.66	25.93	28.22	33.01	3806	1.0
## yrep[6,3]	33.12	0.02	1.03	30.98	32.46	33.13	33.76	35.1	3468	1.0
## yrep[1,4]	26.97	0.03	1.7	23.54	25.91	26.99	28.03	30.4	4186	1.0
## yrep[2,4]	31.4	0.05	3.11	24.94	29.46	31.41	33.4	37.41	3542	1.0
## yrep[3,4]	32.31	0.02	1.34	29.71	31.47	32.33	33.17	34.92	3818	1.0
## yrep[4,4]	26.21	0.04	2.32	21.6	24.78	26.24	27.67	30.76	3532	1.0

## yrep[5,4]	24.48	0.06	3.56	17.4	22.25	24.44	26.73	31.48	3462	1.0
## yrep[6,4]	31.77	0.02	1.0	29.74	31.13	31.79	32.41	33.74	3893	1.0
## yrep[1,5]	27.05	0.03	1.69	23.71	25.99	27.04	28.1	30.43	4040	1.0
## yrep[2,5]	30.5	0.05	3.09	24.38	28.49	30.53	32.54	36.47	3981	1.0
## yrep[3,5]	31.21	0.02	1.35	28.51	30.39	31.21	32.08	33.86	3793	1.0
## yrep[4,5]	25.11	0.04	2.33	20.68	23.59	25.08	26.63	29.64	3954	1.0
## yrep[5,5]	23.1	0.05	3.43	16.42	20.92	23.14	25.22	30.06	4131	1.0
## yrep[6,5]	30.47	0.02	1.03	28.46	29.84	30.45	31.11	32.53	3647	1.0
## yrep[1,6]	27.11	0.03	1.63	23.87	26.07	27.09	28.14	30.34	3968	1.0
## yrep[2,6]	29.61	0.05	3.04	23.58	27.67	29.66	31.53	35.8	4107	1.0
## yrep[3,6]	30.04	0.02	1.34	27.35	29.21	30.05	30.9	32.67	3709	1.0
## yrep[4,6]	23.94	0.04	2.29	19.53	22.47	23.95	25.42	28.56	3965	1.0
## yrep[5,6]	21.65	0.05	3.47	15.0	19.45	21.67	23.81	28.5	4094	1.0
## yrep[6,6]	29.15	0.02	0.99	27.24	28.51	29.15	29.78	31.16	3809	1.0
## yrep[1,7]	27.22	0.03	1.67	23.86	26.17	27.24	28.28	30.5	4040	1.0
## yrep[2,7]	28.68	0.05	3.01	22.67	26.75	28.75	30.59	34.47	3814	1.0
## yrep[3,7]	28.93	0.02	1.33	26.28	28.09	28.92	29.75	31.66	3922	1.0
## yrep[4,7]	22.8	0.04	2.28	18.16	21.35	22.8	24.29	27.25	3565	1.0
## yrep[5,7]	20.12	0.05	3.45	13.24	17.93	20.13	22.31	27.0	4012	1.0
## yrep[6,7]	27.82	0.02	1.0	25.88	27.16	27.82	28.46	29.82	4096	1.0
## yrep[1,8]	27.29	0.03	1.62	24.07	26.26	27.29	28.32	30.57	3993	1.0
## yrep[2,8]	27.81	0.05	3.01	21.7	26.01	27.83	29.7	33.67	4131	1.0
## yrep[3,8]	27.76	0.02	1.32	25.05	26.93	27.76	28.6	30.33	3935	1.0
## yrep[4,8]	21.62	0.03	2.23	17.15	20.2	21.62	23.01	26.02	4162	1.0
## yrep[5,8]	18.71	0.05	3.41	11.94	16.52	18.68	20.92	25.47	3930	1.0
## yrep[6,8]	26.49	0.01	0.99	24.46	25.88	26.49	27.11	28.45	4356	1.0
## yrep[1,9]	27.43	0.03	1.65	24.13	26.39	27.42	28.48	30.78	3860	1.0
## yrep[2,9]	27.03	0.05	3.0	21.07	25.17	27.02	28.89	33.03	3760	1.0
## yrep[3,9]	26.63	0.02	1.32	24.06	25.78	26.62	27.44	29.32	3660	1.0
## yrep[4,9]	20.44	0.04	2.27	16.02	18.99	20.42	21.89	24.93	4086	1.0
## yrep[5,9]	17.19	0.06	3.53	9.89	14.92	17.2	19.41	24.19	3754	1.0
## yrep[6,9]	25.15	0.02	1.01	23.16	24.54	25.15	25.77	27.13	4001	1.0
## yrep[1,10]	27.48	0.03	1.69	24.04	26.44	27.49	28.56	30.81	4108	1.0
## yrep[2,10]	26.18	0.05	3.03	19.9	24.25	26.21	28.09	32.2	4122	1.0
## yrep[3,10]	25.46	0.02	1.34	22.75	24.63	25.45	26.34	28.09	3667	1.0
## yrep[4,10]	19.29	0.04	2.27	14.64	17.89	19.29	20.71	23.79	4049	1.0
## yrep[5,10]	15.75	0.06	3.49	8.82	13.48	15.82	17.97	22.62	3971	1.0
## yrep[6,10]	23.86	0.02	0.99	21.87	23.23	23.85	24.47	25.88	3902	1.0
## yrep[1,11]	27.54	0.03	1.73	24.04	26.48	27.5	28.65	30.89	4106	1.0
## yrep[2,11]	25.26	0.05	3.03	19.21	23.38	25.26	27.17	31.2	3652	1.0
## yrep[3,11]	24.35	0.02	1.32	21.81	23.5	24.3	25.17	27.06	3638	1.0
## yrep[4,11]	18.19	0.04	2.26	13.65	16.76	18.17	19.6	22.78	3930	1.0
## yrep[5,11]	14.28	0.06	3.46	7.3	12.06	14.26	16.46	21.19	3832	1.0
## yrep[6,11]	22.5	0.02	0.99	20.53	21.87	22.5	23.11	24.51	3868	1.0
## yrep[1,12]	27.62	0.03	1.71	24.22	26.55	27.64	28.66	31.06	3861	1.0
## yrep[2,12]	24.27	0.05	3.09	18.01	22.26	24.31	26.29	30.21	3691	1.0
## yrep[3,12]	23.22	0.02	1.33	20.58	22.4	23.2	24.03	25.93	3855	1.0
## yrep[4,12]	17.02	0.04	2.35	12.4	15.52	17.01	18.5	21.95	4039	1.0
## yrep[5,12]	12.91	0.06	3.58	6.07	10.55	12.88	15.25	20.1	4175	1.0
## yrep[6,12]	21.22	0.02	1.01	19.27	20.57	21.2	21.86	23.2	3850	1.0
## yrep[1,13]	27.71	0.03	1.73	24.24	26.61	27.71	28.8	31.14	3951	1.0
## yrep[2,13]	23.48	0.05	3.1	17.41	21.54	23.48	25.4	29.62	3604	1.0
## yrep[3,13]	22.07	0.02	1.34	19.46	21.17	22.07	22.95	24.78	3887	1.0
## yrep[4,13]	15.85	0.04	2.35	11.04	14.39	15.85	17.32	20.49	4072	1.0

```

## yrep[5,13]    11.43    0.06    3.57    4.33    9.19    11.41    13.71    18.65    3992    1.0
## yrep[6,13]    19.88    0.02    1.01    17.88    19.21    19.89    20.55    21.91    4081    1.0
## yrep[1,14]    27.75    0.03    1.79    24.08    26.63    27.78    28.93    31.17    3820    1.0
## yrep[2,14]    22.46    0.05    3.22    16.18    20.39    22.47    24.54    28.67    3915    1.0
## yrep[3,14]    20.92    0.02    1.38    18.12    20.05    20.9    21.78    23.73    3932    1.0
## yrep[4,14]    14.7     0.04    2.42    9.72     13.2    14.75    16.16    19.4     3646    1.0
## yrep[5,14]    9.93     0.06    3.73    2.46     7.52    9.93     12.27    17.55    3827    1.0
## yrep[6,14]    18.56    0.02    1.05    16.45    17.89    18.55    19.23    20.67    3857    1.0
## yrep[1,15]    27.9     0.03    1.78    24.28    26.81    27.94    29.05    31.45    3816    1.0
## yrep[2,15]    21.73    0.05    3.34    15.16    19.64    21.69    23.88    28.27    3795    1.0
## yrep[3,15]    19.8     0.02    1.42    16.92    18.92    19.81    20.67    22.66    3712    1.0
## yrep[4,15]    13.67    0.04    2.44    8.81     12.14    13.69    15.24    18.47    3909    1.0
## yrep[5,15]    8.6      0.06    3.73    1.26     6.28    8.52     10.9     16.01    3901    1.0
## yrep[6,15]    17.24    0.02    1.06    15.11    16.56    17.22    17.91    19.41    3555    1.0
## pred[1]       27.96    0.03    1.86    24.27    26.8    27.97    29.11    31.68    3786    1.0
## pred[2]       20.73    0.05    3.27    14.2     18.59    20.7     22.84    27.23    3687    1.0
## pred[3]       18.67    0.02    1.44    15.92    17.75    18.65    19.55    21.69    3534    1.0
## pred[4]       12.45    0.04    2.49    7.7      10.82    12.45    13.99    17.49    3507    1.0
## pred[5]       7.08     0.07    3.82    -0.53    4.66     7.09     9.49     14.73    3325    1.0
## pred[6]       15.91    0.02    1.06    13.8     15.26    15.89    16.57    18.05    3037    1.0
## lp__          -102.9    0.1     3.76   -111.3   -105.1   -102.5   -100.2   -96.68    1450    1.0

```

```

##
## Samples were drawn using NUTS at Sun 29 Nov 2020 06:48:27 PM .
## For each parameter, n_eff is a crude measure of effective sample size,
## and Rhat is the potential scale reduction factor on split chains (at
## convergence, Rhat=1).

```

```

def get_psis_loo_result(stan_results):
    idata = az.from_pystan(stan_results, log_likelihood="log_lik")
    loo_results = az.loo(idata, pointwise=True)
    print(loo_results)
    khats = loo_results.pareto_k
    az.plot_khat(khats, xlabels=True, annotate=True)

```

```

get_psis_loo_result(stan_results)

```

```

## Computed from 4000 by 90 log-likelihood matrix

```

```

##
##      Estimate      SE
## elpd_loo  -186.24    7.53
## p_loo      15.90      -
##

```

```

## There has been a warning during the calculation. Please check the results.

```

```

## -----

```

```

##

```

```

## Pareto k diagnostic values:

```

```

##              Count  Pct.
## (-Inf, 0.5] (good)    86  95.6%
## (0.5, 0.7]  (ok)      2   2.2%
## (0.7, 1]    (bad)      2   2.2%
## (1, Inf)    (very bad)  0   0.0%

```

```

##

```

```

##

```

```

## /home/weijiang/anaconda3/envs/bda/lib/python3.7/site-packages/arviz/stats/stats.py:684: UserWarning:
## "Estimated shape parameter of Pareto distribution is greater than 0.7 for "

```

```

_ = az.plot_ess(
    stan_results, var_names=["alpha", "beta", "sigma_alpha", "sigma_beta"],
    kind="local", marker="_", ms=20, mew=2, figsize=(20, 20)
)

_ = az.plot_trace(stan_results, var_names = ["alpha", "beta", "sigma_alpha", "sigma_beta"], figsize=(20, 20))

h = stan_results.to_dataframe(diagnostics=True)
print('max treedepth for draws: ', h['treedepth__'].max())

## max treedepth for draws: 6
print('min treedepth for draws: ', h['treedepth__'].min())

## min treedepth for draws: 3
print('mean treedepth for draws: ', h['treedepth__'].mean())

## mean treedepth for draws: 4.05475
print('divergent transitions: ', any(h['divergent__']))

## divergent transitions: False
plt.figure(figsize=(15,10))

## <Figure size 1500x1000 with 0 Axes>
year_idx = np.arange(accident_data.shape[1])+1
actual_years = year_idx + 2004

colors = ['red', 'pink', 'orange', 'gray', 'green', 'purple']
for x in range(1, 7):
    print()
    for i in range(100):
        y = stan_results["beta"][:, x-1][i] * year_idx + stan_results["alpha"][:, x-1][i]
        _ = plt.plot(actual_years, y, color=colors[x-1], alpha=0.05)

for x in range(1, 7):
    for j in reversed(range(1, 16)):
        yrep = stan_results['yrep[{}]',{}].format(x, j)]
        _ = plt.errorbar(
            x = actual_years[j-1],
            y = np.mean(yrep),
            yerr=np.std(yrep),
            fmt='--o', zorder=i+j,
            ecolor='black', capthick=2,
            color='black',
            alpha=0.5
        )

for k in range(1, 7):
    ypred = stan_results['pred[{}]',{}].format(k)]
    _ = plt.errorbar(
        x = 2020,
        y = np.mean(ypred),
        yerr=np.std(ypred),
        fmt='--o', zorder=i+j+100,

```

```

        ecolord='red', capthick=2,
        color='red',
    )

_ = plt.scatter(np.tile(years, 6), accident_data.flatten(), zorder=j+i+100, edgecolors='black')
# _ = plt.scatter(data_for_stan["years"], data_for_stan["accidentData"], zorder=j+i+100, edgecolors='black')
_ = plt.title("Posterior predictive check")
_ = plt.legend(bbox_to_anchor=(1.05, 1), loc='lower left', borderaxespad=0.)

# area_names = ["Metropolitan Police", 'Cumbria', 'Lancashire',
#               'Merseyside', 'Greater Manchester', 'Cheshire']

custom_lines = [
    Line2D([0], [0], color='red', lw=4, label='Metropolitan Police'),
    Line2D([0], [0], color='yellow', lw=4, label='Cumbria'),
    Line2D([0], [0], color='orange', lw=4, label='Lancashire'),
    Line2D([0], [0], color='gray', lw=4, label='Merseyside'),
    Line2D([0], [0], color='green', lw=4, label='Greater Manchester'),
    Line2D([0], [0], color='purple', lw=4, label='Cheshire'),
    Line2D([0], [0], marker='o', color='black', label='Original datapoint', markerfacecolor='b', markeredgewidth=2),
    Line2D([0], [0], marker='o', color='red', label='Predictions 2020', markersize=15),
    Line2D([0], [0], marker='o', color='black', label='Posterior samples', markersize=15),
]

_ = plt.legend(handles=custom_lines, bbox_to_anchor=(1, 1))
_ = plt.xticks(np.arange(2005, 2021), fontsize=13)
_ = plt.yticks(fontsize=14)

data_dict = dict()
names = ["default_prior", "uniform_prior", "bigger_variance"]
for i in range(3):
    current_stan_data = dict(
        N = accident_data.shape[0],
        Y = accident_data.shape[1],
        accidentData = accident_data,
        years = np.arange(1, accident_data.shape[1]+1), # stan index starts from 1
        xpred=2020,
        prior_choice= i+1
    )
    data_dict[names[i]] = current_stan_data

result_dict = dict()
for key, stan_data in data_dict.items():
    print("Generating results with prior:{} {}".format(stan_data["prior_choice"], key))
    sampling_result = stan_model.sampling(data=stan_data)
    #print(sampling_result)
    result_dict[key] = sampling_result

## Generating results with prior:1 default_prior
## Generating results with prior:2 uniform_prior
## Generating results with prior:3 bigger_variance

```

```

_ = az.plot_forest(
    list(result_dict.values()),
    model_names=list(result_dict.keys()), var_names=["beta"], markersize=10,
    kind='ridgeplot', ridgeplot_overlap=3, ridgeplot_alpha=0.3, r_hat=True, ess=True, figsize=(20, 20),
)
plt.rcParams['xtick.labelsize'] = 20
plt.rcParams['ytick.labelsize'] = 20
plt.show()

```

