```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from lifelines import WeibullAFTFitter, LogNormalAFTFitter, LogLogisticAFTFitter, ExponentialFitter
# from Exponential import ExponentialAFTFitter
from lifelines.utils import k_fold_cross_validation
import seaborn as sns
import warnings
```

```
warnings.filterwarnings("ignore")
```

```
start_data = pd.read_csv('telco.csv')
```

```
import pandas as pd

def change(data):
    data_copy = data.copy()
    data_copy.drop(['ID'], axis=1, inplace=True)
    categorical_columns = ['region', 'retire', 'marital', 'ed', 'gender', 'voice', 'internet', 'custcat', 'churn', 'forward'
    data_encoded = pd.get_dummies(data_copy, columns=categorical_columns, drop_first=True)
    data_encoded = data_encoded.rename(columns={'churn_Yes': 'churn'})
    return data_encoded
```

```
data = change(start_data)
data
```

	tenure	age	address	income	region_Zone 2	region_Zone 3	retire_Yes	marital_Unmarried	ed_Did not complete high school	ed_High school degree	ed_ undergra d
0	13	44	9	64	1	0	0	0	0	0	
1	11	33	7	136	0	1	0	0	0	0	
2	68	52	24	116	0	1	0	0	1	0	
3	33	33	12	33	1	0	0	1	0	1	
4	23	30	9	30	1	0	0	0	1	0	
...	...	...	...	...	...	...	...	...	...	...	
995	10	39	0	27	0	1	0	1	0	0	
996	7	34	2	22	0	0	0	1	0	0	
997	67	59	40	944	0	1	0	1	0	0	
998	70	49	18	87	0	1	0	1	0	1	
999	50	36	7	39	0	1	0	0	0	0	

1000 rows × 20 columns

```
weibull_model = WeibullAFTFitter()
log_norm_model = LogNormalAFTFitter()
log_logistic_model = LogLogisticAFTFitter()
#exponential_model = ExponentialAFTFitter()
```

```
weibull = weibull_model.fit(data, duration_col='tenure', event_col='churn')
weibull_pred = weibull.predict_survival_function(data).T
weibull_pred_avg = weibull_pred.mean()
weibull.print_summary()
```

model	lifelines.WeibullAFTFitter
duration col	'tenure'
event col	'churn'
number of observations	1000
number of events observed	274
log-likelihood	-1462.17
time fit was run	2023-11-30 19:04:30 UTC

		coef	exp(coef)	se(coef)	coef lower 95%	coef upper 95%	exp(coef) lower 95%	exp(coef) upper 95%	cmp to	z	p	-log2(p)
lambda_	**address**	0.04	1.04	0.01	0.02	0.06	1.02	1.06	0.00	4.69	<0.005	18.47
	age	0.03	1.03	0.01	0.01	0.04	1.01	1.04	0.00	4.12	<0.005	14.69
	custcat_E-service	0.98	2.66	0.16	0.67	1.28	1.96	3.61	0.00	6.28	<0.005	31.44
	custcat_Plus service	0.74	2.10	0.19	0.36	1.12	1.44	3.06	0.00	3.83	<0.005	12.95
	custcat_Total service	1.00	2.71	0.21	0.58	1.41	1.78	4.11	0.00	4.67	<0.005	18.35
	ed_Did not complete high school	0.44	1.55	0.19	0.06	0.82	1.06	2.27	0.00	2.25	0.02	5.37
	ed_High school degree	0.32	1.38	0.15	0.03	0.61	1.03	1.83	0.00	2.19	0.03	5.14
	ed_Post-undergraduate degree	0.22	1.25	0.19	-0.15	0.60	0.86	1.82	0.00	1.17	0.24	2.05
	ed_Some college	0.25	1.29	0.14	-0.03	0.54	0.97	1.71	0.00	1.75	0.08	3.66
	forward_Yes	-0.10	0.91	0.15	-0.39	0.19	0.68	1.21	0.00	-0.67	0.51	0.98
	gender_Male	0.00	1.00	0.10	-0.20	0.21	0.82	1.23	0.00	0.04	0.97	0.05
	income	0.00	1.00	0.00	-0.00	0.00	1.00	1.00	0.00	1.12	0.26	1.92
	internet_Yes	-0.77	0.46	0.14	-1.04	-0.50	0.35	0.61	0.00	-5.59	<0.005	25.40
	marital_Unmarried	-0.35	0.71	0.10	-0.55	-0.14	0.58	0.87	0.00	-3.32	<0.005	10.13
	region_Zone 2	-0.06	0.94	0.13	-0.31	0.19	0.73	1.21	0.00	-0.49	0.63	0.67
	region_Zone 3	0.12	1.12	0.13	-0.13	0.36	0.87	1.44	0.00	0.91	0.36	1.46
	retire_Yes	0.17	1.19	0.52	-0.85	1.19	0.43	3.30	0.00	0.33	0.74	0.43
	voice_Yes	-0.34	0.72	0.15	-0.63	-0.04	0.53	0.96	0.00	-2.26	0.02	5.38
	Intercept	2.78	16.14	0.27	2.25	3.31	9.48	27.47	0.00	10.25	<0.005	79.48
rho_	**Intercept**	0.17	1.19	0.05	0.07	0.27	1.08	1.32	0.00	3.42	<0.005	10.66

Concordance	0.78
AIC	2964.34
log-likelihood ratio test	288.52 on 18 df

```
log_norm = log_norm_model.fit(data, duration_col='tenure', event_col='churn')
log_norm_pred = log_norm.predict_survival_function(data).T
log_norm_pred_avg = log_norm_pred.mean()
log_norm.print_summary()
```

model	lifelines.LogNormalAFTFitter
duration col	'tenure'
event col	'churn'
number of observations	1000
number of events observed	274
log-likelihood	-1457.01
time fit was run	2023-11-30 19:04:33 UTC

		coef	exp(coef)	se(coef)	coef lower 95%	coef upper 95%	exp(coef) lower 95%	exp(coef) upper 95%	cmp to	z	p	-log2(p)
mu_	**address**	0.04	1.04	0.01	0.03	0.06	1.03	1.06	0.00	4.78	<0.005	19.11
	age	0.03	1.03	0.01	0.02	0.05	1.02	1.05	0.00	4.50	<0.005	17.19
	custcat_E-service	1.07	2.90	0.17	0.73	1.40	2.08	4.06	0.00	6.25	<0.005	31.21
	custcat_Plus service	0.92	2.52	0.22	0.50	1.35	1.65	3.85	0.00	4.29	<0.005	15.75
	custcat_Total service	1.20	3.32	0.25	0.71	1.69	2.03	5.42	0.00	4.79	<0.005	19.16
	ed_Did not complete high school	0.37	1.45	0.20	-0.02	0.77	0.98	2.16	0.00	1.85	0.06	3.97
	ed_High school degree	0.32	1.37	0.16	-0.00	0.64	1.00	1.89	0.00	1.94	0.05	4.24
	ed_Post-undergraduate degree	-0.03	0.97	0.22	-0.47	0.40	0.62	1.50	0.00	-0.15	0.88	0.19
	ed_Some college	0.27	1.31	0.17	-0.05	0.60	0.95	1.82	0.00	1.65	0.10	3.33
	forward_Yes	-0.20	0.82	0.18	-0.55	0.15	0.58	1.17	0.00	-1.10	0.27	1.88
	gender_Male	0.05	1.05	0.11	-0.17	0.28	0.84	1.32	0.00	0.45	0.65	0.62
	income	0.00	1.00	0.00	-0.00	0.00	1.00	1.00	0.00	1.52	0.13	2.95
	internet_Yes	-0.77	0.46	0.14	-1.05	-0.49	0.35	0.61	0.00	-5.38	<0.005	23.65
	marital_Unmarried	-0.46	0.63	0.12	-0.68	-0.23	0.51	0.80	0.00	-3.94	<0.005	13.60
	region_Zone 2	-0.10	0.91	0.14	-0.38	0.18	0.69	1.20	0.00	-0.68	0.50	1.01
	region_Zone 3	0.05	1.05	0.14	-0.23	0.33	0.80	1.38	0.00	0.34	0.73	0.45
	retire_Yes	0.02	1.02	0.44	-0.85	0.89	0.43	2.44	0.00	0.05	0.96	0.06
	voice_Yes	-0.43	0.65	0.17	-0.76	-0.10	0.47	0.90	0.00	-2.57	0.01	6.61
	Intercept	2.36	10.61	0.29	1.79	2.94	5.98	18.84	0.00	8.07	<0.005	50.37
sigma_	**Intercept**	0.28	1.32	0.05	0.19	0.37	1.20	1.44	0.00	6.00	<0.005	28.87

Concordance	0.79
AIC	2954.02
log-likelihood ratio test	291.01 on 18 df

```
log_log = log_logistic_model.fit(data, duration_col='tenure', event_col='churn')
log_log_pred = log_log.predict_survival_function(data).T
log_log_pred_avg = log_log_pred.mean()
log_log.print_summary()
```

model	lifelines.LogLogisticAFTFitter
duration col	'tenure'
event col	'churn'
number of observations	1000
number of events observed	274
log-likelihood	-1458.10
time fit was run	2023-11-30 19:04:35 UTC

		coef	exp(coef)	se(coef)	coef lower 95%	coef upper 95%	exp(coef) lower 95%	exp(coef) upper 95%
alpha_	**address**	0.04	1.04	0.01	0.02	0.06	1.02	1.06
	age	0.03	1.03	0.01	0.02	0.05	1.02	1.05
	custcat_E-service	1.04	2.83	0.17	0.72	1.36	2.05	3.91
	custcat_Plus service	0.86	2.37	0.21	0.45	1.27	1.57	3.57
	custcat_Total service	1.20	3.33	0.24	0.73	1.67	2.08	5.34
	ed_Did not complete high school	0.43	1.54	0.20	0.04	0.82	1.05	2.28
	ed_High school degree	0.34	1.40	0.15	0.03	0.64	1.03	1.89
	ed_Post-undergraduate degree	-0.02	0.98	0.22	-0.45	0.40	0.64	1.49
	ed_Some college	0.24	1.27	0.16	-0.06	0.55	0.94	1.73
	forward_Yes	-0.19	0.82	0.17	-0.53	0.14	0.59	1.15
	gender_Male	0.04	1.04	0.11	-0.18	0.26	0.84	1.29
	income	0.00	1.00	0.00	-0.00	0.00	1.00	1.00
	internet_Yes	-0.80	0.45	0.14	-1.07	-0.52	0.34	0.60
	marital_Unmarried	-0.45	0.64	0.11	-0.66	-0.23	0.52	0.80
	region_Zone 2	-0.05	0.95	0.14	-0.31	0.22	0.73	1.24
	region_Zone 3	0.11	1.12	0.14	-0.15	0.38	0.86	1.46
	retire_Yes	0.06	1.06	0.48	-0.87	1.00	0.42	2.71
	voice_Yes	-0.40	0.67	0.16	-0.72	-0.08	0.49	0.92
	Intercept	2.33	10.33	0.28	1.78	2.89	5.95	17.93
beta_	**Intercept**	0.34	1.40	0.05	0.24	0.44	1.27	1.55

Concordance	0.79
AIC	2956.21

Exponential

```
# exponential = exponential_model.fit(data, duration_col='tenure', event_col='churn')
# exponential_pred = exponential.predict_survival_function(data).T
# exponential_pred_avg = exponential_pred.mean()
# exponential.print_summary()
```

Comparing With AIC

```
# print(f'Exponential AIC: {exponential.AIC_}')
print(f'Log-Normal AIC: {log_norm.AIC_}')
print(f'Log-Logistic AIC: {log_log.AIC_}')
print(f'Weibull AIC: {weibull.AIC_}')
#'Exponential': exponential.AIC_,
scores = {'Log-normal': log_norm.AIC_, 'Log-logistic': log_log.AIC_, 'Weibull': weibull.AIC_}
print(f'\nThe best model based on AIC scores is: \033[1m{min(scores, key=scores.get)}\033[0m')
```

```
Log-Normal AIC: 2954.0240102517128
Log-Logistic AIC: 2956.2085614433336
Weibull AIC: 2964.3432480838806

The best model based on AIC scores is: Log-normal
```

Other than the AIC score and the plots, there are some other important factors to consider before choosing the best model.

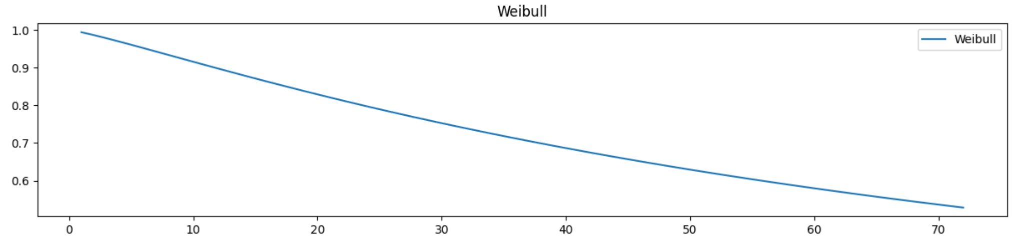
When we look at the number of parameters we can understand the complexity of the model. For example, the exponential model has only 1 parameter, while weibull has 2, and Log Normal and Log Logistic models both have 3.

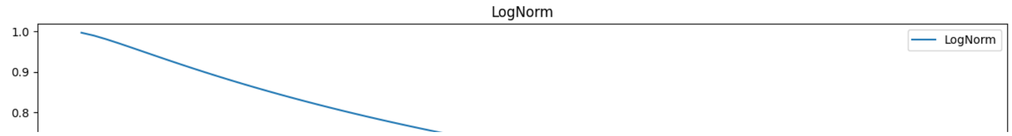
Another criteria is the Hazard Rate. In this case Weibull model is preffered over the other ones as it has the ability to capture both increasing and decreasing hazard rates.

I am going to trust the AIC score and go with the best performing model which is the Log-Normal model.

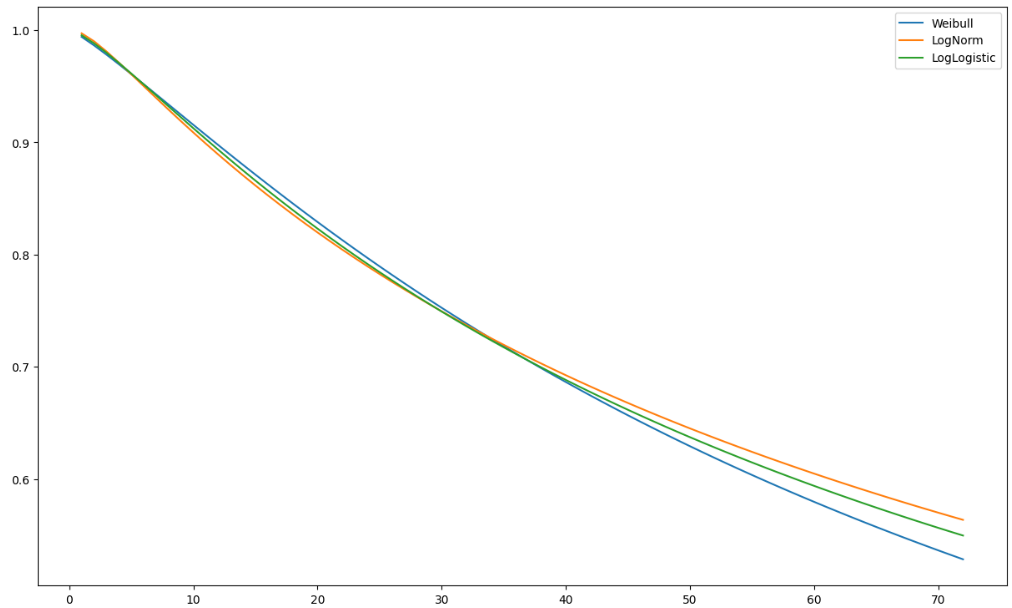
```
import matplotlib.pyplot as plt

def plot_prediction(prediction, label):
    plt.figure(figsize=(15, 3))
    plt.plot(prediction, label=label)
    plt.legend()
    plt.title(label)
    plt.show()
```

```
plot_prediction(weibull_pred_avg, 'Weibull')
plot_prediction(log_norm_pred_avg, 'LogNorm')
plot_prediction(log_log_pred_avg, 'LogLogistic')
```






```
plt.figure(figsize=(15,9))
plt.plot(weibull_pred_avg, label='Weibull')
plt.plot(log_norm_pred_avg, label='LogNorm')
plt.plot(log_log_pred_avg, label='LogLogistic')
# plt.plot(exponential_pred_avg, label='Exponential')
plt.legend()
plt.show()
```



We will keep the features that are important for calculating the CLV

```
important_cols = ["address", "age", "internet_Yes", "marital_Unmarried", "tenure", "churn", "custcat_E-service", "custcat_
```

```
changed = data[important_cols]
changed
```

	address	age	internet_Yes	marital_Unmarried	tenure	churn	custcat_E-service	custcat_P serv
0	9	44	0	0	13	1	0	
1	7	33	0	0	11	1	0	
2	24	52	0	0	68	0	0	
3	12	33	0	1	33	1	0	
4	9	30	0	0	23	0	0	
...	...	...	...	...	...	...	...	
995	0	39	0	1	10	0	0	
996	2	34	0	1	7	0	0	
997	40	59	1	1	67	0	0	
998	18	49	0	1	70	0	0	

```
log_norm = log_norm_model.fit(changed, duration_col='tenure', event_col='churn')
log_norm_pred = log_norm.predict_survival_function(changed).T
log_norm_pred_avg = log_norm_pred.mean()
log_norm.print_summary()
```

model	lifelines.LogNormalAFTFitter
duration col	'tenure'
event col	'churn'
number of observations	1000
number of events observed	274
log-likelihood	-1462.10
time fit was run	2023-11-30 19:04:40 UTC

		coef	exp(coef)	se(coef)	coef lower 95%	coef upper 95%	exp(coef) lower 95%	exp(coef) upper 95%
mu_	**address**	0.04	1.04	0.01	0.03	0.06	1.03	1.06
	age	0.04	1.04	0.01	0.02	0.05	1.02	1.05
	custcat_E-service	1.03	2.79	0.17	0.69	1.36	2.00	3.89
	custcat_Plus service	0.82	2.28	0.17	0.49	1.15	1.63	3.17
	custcat_Total service	1.01	2.75	0.21	0.60	1.42	1.83	4.15
	internet_Yes	-0.84	0.43	0.14	-1.11	-0.57	0.33	0.57
	marital_Unmarried	-0.45	0.64	0.11	-0.67	-0.22	0.51	0.80
	voice_Yes	-0.46	0.63	0.17	-0.79	-0.14	0.45	0.87
	Intercept	2.53	12.62	0.24	2.06	3.01	7.84	20.30
sigma_	**Intercept**	0.28	1.33	0.05	0.19	0.37	1.21	1.45

Concordance	0.79
AIC	2944.20
log-likelihood ratio test	280.83 on 8 df
-log2(p) of ll-ratio test	183.73

CLV

```
clv_df = log_norm_pred.copy()
```

Choosing values for calculations

```
margin = 1200
seq = range(1,len(clv_df.columns)+1)
r = 0.2
```

```
for i in seq:
    clv_df.loc[:, i] = clv_df.loc[:, i]/((1+r/12)**(seq[i-1]-1))
```

```
clv_df["CLV"] = margin * clv_df.sum(axis = 1)
clv_df
```

	1.0	2.0	3.0	4.0	5.0	6.0	7.0	8.0	9
0	0.999688	0.981766	0.962887	0.943312	0.923291	0.903030	0.882686	0.862382	0.8422
1	0.999736	0.982011	0.963448	0.944262	0.924671	0.904857	0.884962	0.865099	0.8453
2	0.999999	0.983595	0.967439	0.951520	0.935830	0.920363	0.905115	0.890083	0.8752
3	0.997985	0.974462	0.947865	0.919716	0.890961	0.862184	0.833749	0.805882	0.7787
4	0.999870	0.982748	0.965194	0.947289	0.929147	0.910870	0.892550	0.874261	0.8560
...	...	...	...	...	...	...	...	...	
995	0.996036	0.967408	0.934758	0.900580	0.866204	0.832351	0.799415	0.767609	0.7370
996	0.995073	0.964167	0.928987	0.892408	0.855880	0.820150	0.785604	0.752433	0.7207
997	0.999991	0.983523	0.967215	0.951047	0.935016	0.919124	0.903378	0.887785	0.8723
998	0.999923	0.983062	0.965975	0.948693	0.931279	0.913801	0.896318	0.878885	0.8615
999	0.999471	0.980695	0.960507	0.939367	0.917660	0.895676	0.873628	0.851674	0.8299

1000 rows × 73 columns

```
start_data["CLV"] = clv_df.CLV
```

From these results we can understand that the customers who have higher CLV are the ones with low Churn risk.

```
print(start_data.groupby(["gender", "ed","marital"])[["CLV"]].mean())

print(start_data.groupby("gender")[["CLV"]].mean())
print(start_data.groupby("voice")[["CLV"]].mean())
print(start_data.groupby("retire")[["CLV"]].mean())
print(start_data.groupby("internet")[["CLV"]].mean())
print(start_data.groupby("marital")[["CLV"]].mean())
print(start_data.groupby("ed")[["CLV"]].mean())
print(start_data.groupby("custcat")[["CLV"]].mean())
print(start_data.groupby("forward")[["CLV"]].mean())
print(start_data.groupby("region")[["CLV"]].mean())
```

```
       High school degree           Married    41730.812079
                                    Unmarried  38798.258151
       Post-undergraduate degree    Married    41469.846423
                                    Unmarried  33163.532137
       Some college                 Married    39603.312317
                                    Unmarried  38833.030233
Male   College degree               Married    40474.492643
                                    Unmarried  34019.819116
       Did not complete high school Married    45561.598988
                                    Unmarried  41463.351385
       High school degree           Married    43968.687565
                                    Unmarried  37981.109920
       Post-undergraduate degree    Married    39875.514579
                                    Unmarried  32513.981805
       Some college                 Married    42316.153044
                                    Unmarried  34509.977140
                 CLV
gender
Female  39574.507205
Male    39739.438987
                CLV
voice
No     40842.419256
Yes    36933.702151
                 CLV
retire
No      39205.937819
Yes     48742.776901
                   CLV
internet
No        42680.596692
Yes       34456.609094
                    CLV
marital
Married    41727.521111
Unmarried  37621.873874
                                      CLV
ed
College degree                37282.113864
Did not complete high school  43090.375633
High school degree            40465.491608
Post-undergraduate degree     37025.916941
Some college                  38671.824752
                        CLV
custcat
Basic service  34058.542033
E-service      42599.450472
Plus service   44506.984869
Total service  37474.803282
                  CLV
forward
No       38314.196841
Yes      41032.193626
                 CLV
region
Zone 1  39728.184574
Zone 2  40099.577397
Zone 3  39152.427245
```

The most noticeable difference in Customer Lifetime Value (CLV) is observed when considering the "retire" variable. This can be explained by the fact that older people are more conservative and tend to rely on the product that they are using. I could find a group with a high CLV. Those are the males who did not finish the high school and are married. In avarage they have around 45500 of CLV. I think that this has to do with the stability in their lives and the influence they might have on the surrounding people.

Conclusion

From our data we could understand that the higher is the CLV, the lower is the risk of churn.

The coefficients in our analysis carry specific implications:

- Positive coefficients signify that an increase in a given variable positively influences the anticipated customer lifetime.
- Negative coefficients indicate that an increase in a specific variable leads to a decrease in the expected customer lifetime.
- The magnitude of the coefficient reflects the strength of the variable's impact on customer lifetime.

For effective retention strategies based on CLV scores:

As the younger segment has lower CLV:

- Actively listen to customer feedback and address concerns promptly, particularly for the younger demographic.
- Implement exclusive discounts, special offers, or other perks for loyal customers, with a specific focus on the younger age group.
- Work on the internet quality, do better customer support for internet users, as the CLV of the people who use internet are low.

Budget

We will set values for retention rate and cost per customer

```
changed["CLV"] = clv_df["CLV"]
cust_retained = changed[changed['churn'] == 0]
retained_clv = cust_retained['CLV'].sum()

retention_rate = 0.7
cost_per_customer = 3500
cost_retention = len(changed) * retention_rate * cost_per_customer

budget = retained_clv - cost_retention

print("BUDGET:", budget)
```

```
BUDGET: 27693477.23765699
```

For the numbers that we set this will be our budget for 1 Year.