

AADT Prediction Model using PyTorch

This notebook demonstrates how to use PyTorch to predict Annual Average Daily Traffic (AADT) using winter-related features.

```
In [22]: import pandas as pd
import torch
import torch.nn as nn
import torch.optim as optim
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt
import statsmodels.api as sm
import seaborn as sns

# 1. Load dataset
use_cols = ["AADT", "snow_depth", "SpeedLimit", "SHAPE_Leng"]
df = pd.read_excel("AADT_with_snow.xlsx", usecols=use_cols)
df = df.dropna()
```

```
In [24]: # Step 1: Define snowfall category (0-5, 5-10, ..., 30-35 inches)
def snow_category(inches):
    if inches < 0: return "baseline"
    elif inches <= 5: return "CC1"
    elif inches <= 10: return "CC2"
    elif inches <= 15: return "CC3"
    elif inches <= 20: return "CC4"
    elif inches <= 25: return "CC5"
    elif inches <= 30: return "CC6"
    else: return "CC7"

# Assign snow categories
df["SnowCat"] = df["snow_depth"].apply(snow_category)

# Create dummy variables (CC1-CC7)
dummies = pd.get_dummies(df["SnowCat"])
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# Replace 'baseline' with Speed_Limit in the design matrix
X = pd.concat([dummies.drop(columns=["baseline"], errors='ignore').astype(float), df[["SpeedLimit", "SHAPE"]], axis=1)
X = sm.add_constant(X)
y = df["AADT"].astype(float)

# Fit OLS regression
model = sm.OLS(y, X).fit()
print(model.summary())

# Visualize coefficients
plt.figure(figsize=(10, 6))
sns.barplot(x=model.params.index[1:], y=model.params.values[1:])
plt.axhline(0, color='gray', linestyle='--')
plt.ylabel("Effect on AADT")
plt.title("Estimated Impact of Snowfall Categories on AADT")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

OLS Regression Results

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Dep. Variable:          AADT      R-squared:                0.104
Model:                  OLS      Adj. R-squared:           0.104
Method:                 Least Squares      F-statistic:          255.3
Date:                   Mon, 05 May 2025    Prob (F-statistic):      0.00
Time:                   01:24:32    Log-Likelihood:         -1.9746e+05
No. Observations:       19740      AIC:                   3.949e+05
Df Residuals:           19730      BIC:                   3.950e+05
Df Model:               9
Covariance Type:        nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
const	-3.497e+04	995.210	-35.137	0.000	-3.69e+04	-3.3e+04
CC1	-889.4267	492.127	-1.807	0.071	-1854.037	75.183
CC2	-3024.0298	505.265	-5.985	0.000	-4014.392	-2033.668
CC3	-2740.9609	537.720	-5.097	0.000	-3794.938	-1686.984
CC4	-2884.1054	623.050	-4.629	0.000	-4105.336	-1662.875
CC5	-3153.8856	1052.245	-2.997	0.003	-5216.375	-1091.396
CC6	-3186.9728	1265.871	-2.518	0.012	-5668.186	-705.759
CC7	-3348.2282	3126.452	-1.071	0.284	-9476.337	2779.881
SpeedLimit	709.8023	15.756	45.049	0.000	678.919	740.686
SHAPE_Leng	-0.1078	0.011	-9.555	0.000	-0.130	-0.086

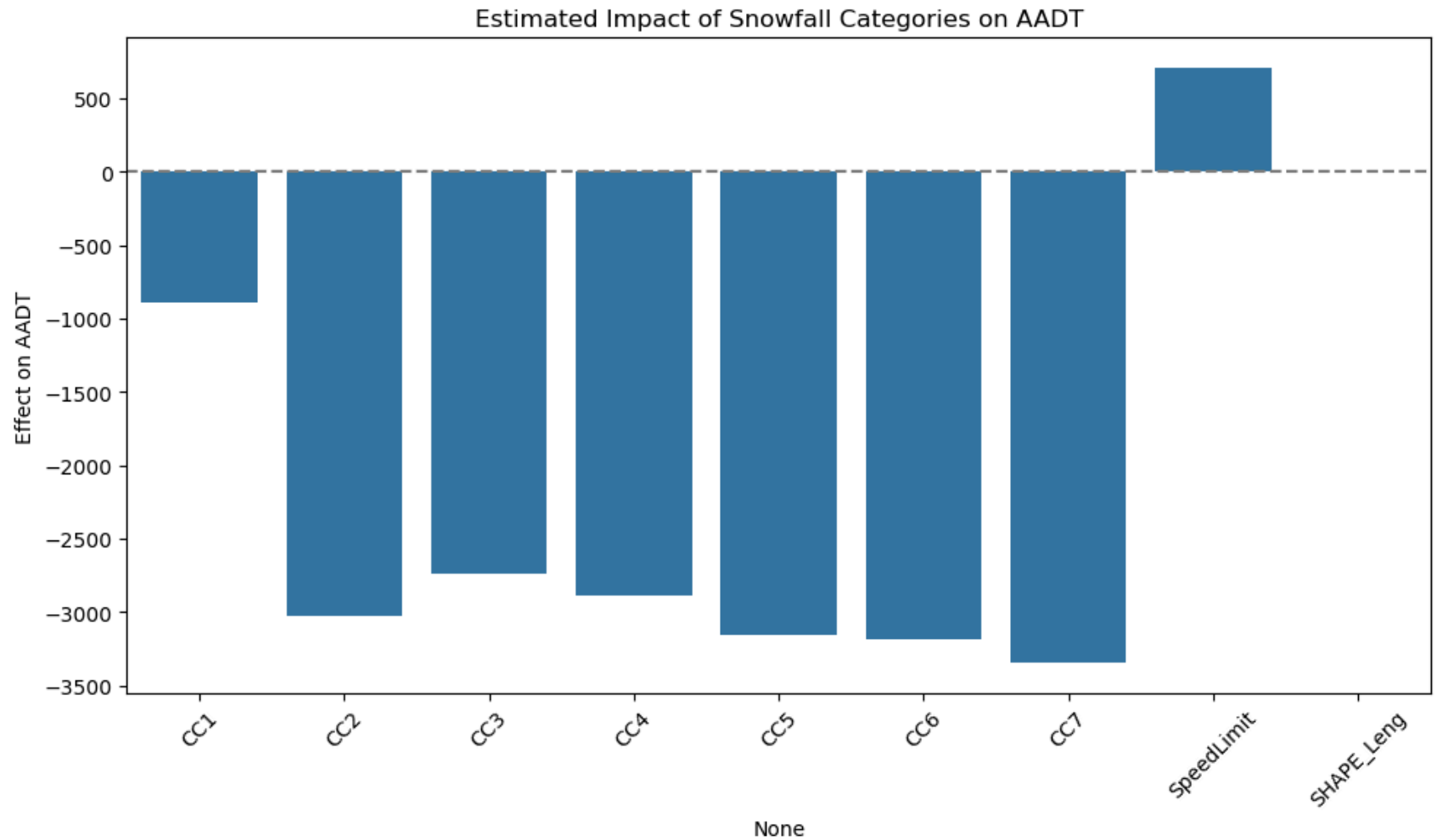
```

=====
Omnibus:                21553.277    Durbin-Watson:          1.187
Prob(Omnibus):           0.000      Jarque-Bera (JB):       2280616.626
Skew:                    5.518      Prob(JB):               0.00
Kurtosis:                54.488      Cond. No.               4.20e+05
=====

```

Notes:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 4.2e+05. This might indicate that there are strong multicollinearity or other numerical problems.



```
In [26]: # Select feature matrix and label
torch_X = X.drop(columns="const").values # drop intercept
scaler_X = StandardScaler()
scaler_y = StandardScaler()
X_scaled = scaler_X.fit_transform(torch_X)
y_scaled = scaler_y.fit_transform(y.values.reshape(-1, 1))

X_tensor = torch.tensor(X_scaled, dtype=torch.float32)
y_tensor = torch.tensor(y_scaled, dtype=torch.float32)

# 5. Train/test split
```

```
X_train, X_test, y_train, y_test = train_test_split(X_tensor, y_tensor, test_size=0.2, random_state=42)

# 6. Define model
class AADTModel(nn.Module):
    def __init__(self):
        super().__init__()
        self.net = nn.Sequential(
            nn.Linear(X_tensor.shape[1], 64),
            nn.ReLU(),
            nn.Linear(64, 32),
            nn.ReLU(),
            nn.Linear(32, 1)
        )
    def forward(self, x):
        return self.net(x)

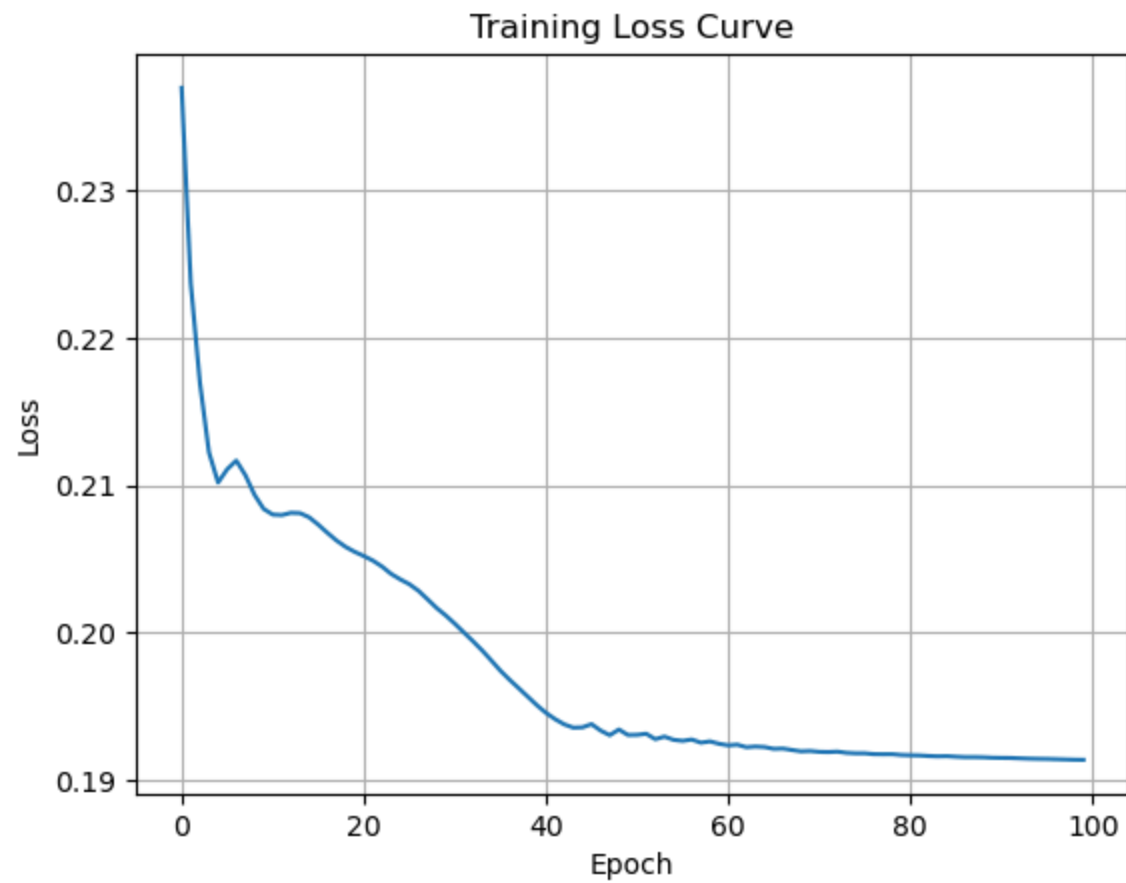
model = AADTModel()
criterion = nn.SmoothL1Loss() # Huber Loss
optimizer = optim.Adam(model.parameters(), lr=0.01)

# === Training ===
loss_values = []
for epoch in range(100):
    model.train()
    optimizer.zero_grad()
    outputs = model(X_train)
    loss = criterion(outputs, y_train)
    loss.backward()
    optimizer.step()
    loss_values.append(loss.item())
    if (epoch + 1) % 10 == 0:
        print(f"Epoch {epoch+1}/100, Loss: {loss.item():.4f}")

# Plot loss curve
plt.figure()
plt.plot(loss_values)
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.title("Training Loss Curve")
plt.grid(True)
plt.show()
```

```
# Final test evaluation
model.eval()
with torch.no_grad():
    y_pred_test = model(X_test)
    test_loss = criterion(y_pred_test, y_test)
    print(f"Final Test Loss: {test_loss.item():.4f}")
```

```
Epoch 10/100, Loss: 0.2084
Epoch 20/100, Loss: 0.2055
Epoch 30/100, Loss: 0.2012
Epoch 40/100, Loss: 0.1951
Epoch 50/100, Loss: 0.1931
Epoch 60/100, Loss: 0.1925
Epoch 70/100, Loss: 0.1920
Epoch 80/100, Loss: 0.1917
Epoch 90/100, Loss: 0.1915
Epoch 100/100, Loss: 0.1914
```



Final Test Loss: 0.2116

In []: