DT503_4_Accident_Predictions_Walkthrough

December 2, 2024

1 DT503.4 Traffic Accident Risk Prediction

1.1 Overview

This notebook implements advanced time series analysis techniques to create a practical model for predicting traffic accident risks. We'll learn how to:

- Analyse temporal patterns in accident data
- Implement multiple forecasting approaches (SARIMA and Prophet)
- Create a production-ready prediction model

1.1.1 Required Libraries

[1]:
```python
# Import required libraries
import pandas as pd
import numpy as np
from prophet import Prophet
from statsmodels.tsa.statespace.sarimax import SARIMAX
from sklearn.metrics import mean_squared_error, mean_absolute_error
import matplotlib.pyplot as plt
from typing import Dict
from datetime import datetime

# Set display options
pd.set_option('display.max_columns', None)
pd.set_option('display.expand_frame_repr', False)
```

1.2 Data Loading and Preparation

First, let's define our TimeSeriesAnalyser class that will handle all our analysis:

[2]:
```python
class TimeSeriesAnalyser:
    """Handles time series analysis of accident data."""

    def __init__(self):
        self.prophet_model = None
        self.sarima_model = None
        self.seasonal_patterns = {}
        self.weather_columns = None
```

```
        self.weather_means = None

    def analyse_seasonality(self, data: pd.DataFrame) -> Dict:
        """ Analyse seasonal patterns in the data.
            This method groups the data by key temporal features (hour, day, month)
            to identify trends like peak accident times.
        """
        # Group data by hour of the day and count occurrences
        patterns = {
            'hourly': data.groupby('hour').size(),
            'daily': data.groupby('day_of_week').size(),
            'monthly': data.groupby('month').size()
        }

        # Find the peak periods (maximum occurrences)
        # E.g., Peak hour is the hour with the highest accident count
        self.seasonal_patterns = {
            'peak_hour': patterns['hourly'].idxmax(),
            'peak_day': patterns['daily'].idxmax(),
            'peak_month': patterns['monthly'].idxmax()
        }

        return self.seasonal_patterns

    # Method to evaluate the performance of the model

    def visualise_seasonality(self, data: pd.DataFrame):
        """Create visualisations of seasonal patterns."""
        fig, (ax1, ax2, ax3) = plt.subplots(3, 1, figsize=(15, 12))

        # Hourly pattern
        hourly = data.groupby('hour').size()
        ax1.bar(hourly.index, hourly.values, color='skyblue')
        ax1.set_title('Hourly Distribution of Accidents')
        ax1.set_xlabel('Hour of Day')
        ax1.set_ylabel('Number of Accidents')
        ax1.grid(True, alpha=0.3)

        # Daily pattern
        daily = data.groupby('day_of_week').size()
        days = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday', 'Sunday']
        ax2.bar(days, daily.values, color='lightgreen')
        ax2.set_title('Daily Distribution of Accidents')
        ax2.set_xlabel('Day of Week')
        ax2.set_ylabel('Number of Accidents')
```

```
        plt.setp(ax2.xaxis.get_majorticklabels(), rotation=45)
        ax2.grid(True, alpha=0.3)

        # Monthly pattern
        monthly = data.groupby('month').size()
        months = ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun',
                  'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec']
        ax3.bar(months, monthly.values, color='salmon')
        ax3.set_title('Monthly Distribution of Accidents')
        ax3.set_xlabel('Month')
        ax3.set_ylabel('Number of Accidents')
        plt.setp(ax3.xaxis.get_majorticklabels(), rotation=45)
        ax3.grid(True, alpha=0.3)

        plt.tight_layout()
        plt.show()

        # Print summary statistics
        print("\nSeasonal Pattern Summary:")
        print(f"Peak hour: {self.seasonal_patterns['peak_hour']:02d}:00")
        print(f"Peak day: {days[self.seasonal_patterns['peak_day']]}")
        print(f"Peak month: {months[self.seasonal_patterns['peak_month']-1]}")



    def fit_prophet(self, data: pd.DataFrame):
        """Implement Prophet model for accident prediction.
        This includes adding weather as regressors and training the model.
        """
        # Prepare data for Prophet
        # Prophet expects columns named 'ds' (datetime) and 'y' (target value)
        prophet_data = data.groupby('date').size().reset_index()
        prophet_data.columns = ['ds', 'y']

        # Add weather regressors as additional features
        # Convert weather conditions into one-hot encoded features
        weather_dummies = pd.get_dummies(data['weather_conditions'],␣
↪prefix='weather')
        daily_weather = weather_dummies.groupby(data['date']).mean()
        prophet_data = prophet_data.join(daily_weather, on='ds')

        # Store weather columns for prediction
        self.weather_columns = daily_weather.columns
        self.weather_means = daily_weather.mean()

        # Initialise Prophet model with seasonalities
```

```python
        # 'Multiplicative' mode accounts for interaction between trends and␣
↪seasonality
        self.prophet_model = Prophet(
            yearly_seasonality=True,
            weekly_seasonality=True,
            daily_seasonality=True,
            seasonality_mode='multiplicative'
        )

        # Add weather regressors
        for column in self.weather_columns:
            self.prophet_model.add_regressor(str(column))

        # Fit the model
        self.prophet_model.fit(prophet_data)

    def fit_sarima(self, data: pd.DataFrame):
        """
        Implement SARIMA model for time series forecasting.
        This method uses fixed parameters but can be tuned based on the dataset.
        """
        # Prepare daily counts
        daily_counts = data.groupby('date').size()

        # SARIMA model with parameters
        # order=(p, d, q): ARIMA terms
        # seasonal_order=(P, D, Q, s): Seasonal terms, where 's' is the␣
↪seasonal period
        # Example parameters chosen based on data's weekly and monthly patterns
        self.sarima_model = SARIMAX(
            daily_counts,
            order=(2, 1, 1),
            seasonal_order=(1, 1, 1, 12)
        )

        # Fit the model
        self.sarima_results = self.sarima_model.fit()

    def predict_prophet(self, dates):
        """Make Prophet predictions including weather regressors."""
        future = pd.DataFrame({'ds': dates})

        # Add weather regressors with mean values
        for column in self.weather_columns:
            future[column] = self.weather_means[column]

        return self.prophet_model.predict(future)
```

1.3 Data Loading and Validation

Here, we load and validate accident data, ensuring proper formatting and quality. We also create features like time, date and weather-related columns to enrich the dataset for analysis.

Let's create a function to load and validate our data, ensuring proper formatting:

[3]:
```python
def load_and_validate_data(filepath: str) -> pd.DataFrame:
    """Load and validate accident data.

    Args:
        filepath: Path to accident data CSV

    Returns:
        Validated DataFrame with proper datetime handling
    """
    try:
        # Load the data
        data = pd.
↪read_csv('dft-road-casualty-statistics-collision-2023_Devon_and_Cornwall.
↪csv')

        # Validate required columns
        required_cols = [
            'date', 'time', 'latitude', 'longitude',
            'weather_conditions', 'road_type'
        ]

        if not all(col in data.columns for col in required_cols):
            raise ValueError(f"Missing required columns: {required_cols}")

        # Convert dates and add temporal features
        data['date'] = pd.to_datetime(data['date'], format='%d/%m/%Y')
        data['hour'] = pd.to_datetime(data['time'], format='%H:%M').dt.hour
        data['month'] = data['date'].dt.month
        data['day_of_week'] = data['date'].dt.dayofweek
        data['is_weekend'] = data['day_of_week'].isin([5, 6]).astype(int)

        # Print data quality report
        print("Data Quality Report:")
        print(f"Date range: {data['date'].min()} to {data['date'].max()}")
        print(f"Total records: {len(data)}")
        print(f"Missing values: {data.isnull().sum().sum()}")

        return data

    except Exception as e:
        raise Exception(f"Error processing data: {str(e)}")
```

Let's explore accident data trends across hours, days and months to identify peak periods. Visualisations highlight key seasonal patterns influencing accident risks.

We'll also train two time series models: SARIMA and Prophet and incorporate weather and seasonal factors to accurately forecast accident risks.

[4]:
```
# Load the accident data
data = load_and_validate_data('accident_data.csv')

# Initialise analyser
analyser = TimeSeriesAnalyser()

# Analyse and visualise seasonal patterns
patterns = analyser.analyse_seasonality(data)
analyser.visualise_seasonality(data)

# Train models
print("Training models...")
analyser.fit_prophet(data)
analyser.fit_sarima(data)
print("Training complete!")
```

```
Data Quality Report:
Date range: 2023-01-02 00:00:00 to 2023-12-31 00:00:00
Total records: 2806
Missing values: 0
```


```
12:03:17 - cmdstanpy - INFO - Chain [1] start processing


Seasonal Pattern Summary:
Peak hour: 17:00
Peak day: Friday
Peak month: Jul
Training models…

12:03:17 - cmdstanpy - INFO - Chain [1] done processing
c:\Users\garet\Documents\GitHub\DT503\env\Lib\site-
packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: A date index has
been provided, but it has no associated frequency information and so will be
ignored when e.g. forecasting.
  self._init_dates(dates, freq)
c:\Users\garet\Documents\GitHub\DT503\env\Lib\site-
packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: A date index has
been provided, but it has no associated frequency information and so will be
ignored when e.g. forecasting.
  self._init_dates(dates, freq)
```

```
c:\Users\garet\Documents\GitHub\DT503\env\Lib\site-
packages\statsmodels\tsa\statespace\sarimax.py:978: UserWarning: Non-invertible
starting MA parameters found. Using zeros as starting parameters.
  warn('Non-invertible starting MA parameters found.'
```

```
Training complete!
```

Both models are trained, utilising temporal and weather-related features and are ready for prediction and evaluation.

1.4 Model Predictions

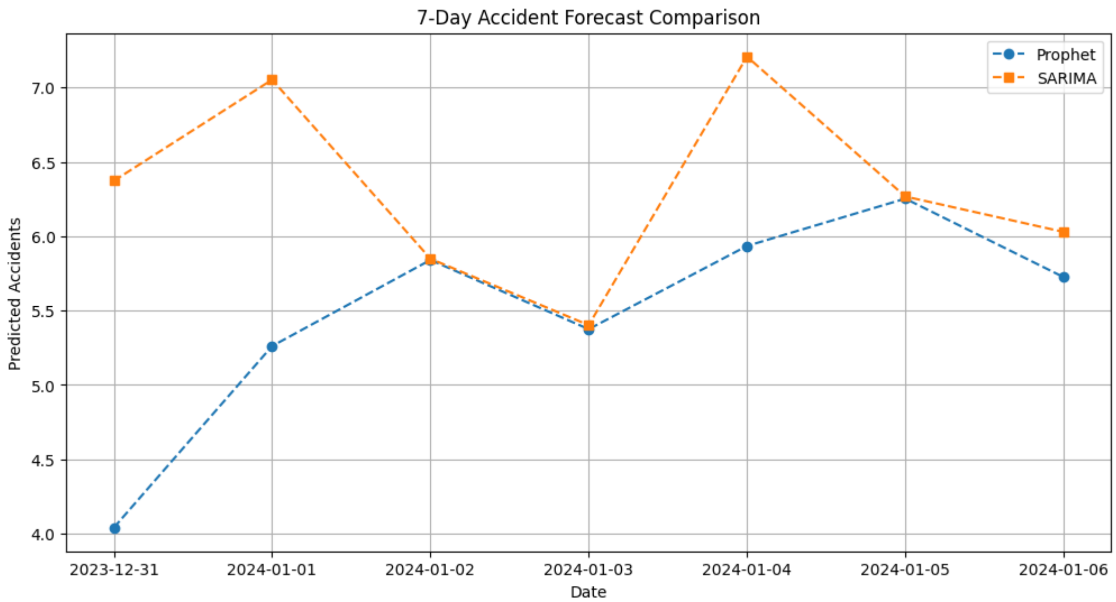
We can now generate accident risk forecasts using SARIMA and Prophet models for future dates. These predictions highlight potential risk factors under varying conditions.

Let's generate and compare predictions from both models:

[5]:
```python
# Generate future dates
future_dates = pd.date_range(
    start=data['date'].max(),
    periods=7,
    freq='D'
)

# Get predictions
prophet_forecast = analyser.predict_prophet(future_dates)
sarima_forecast = analyser.sarima_results.forecast(7)

# Plot results
plt.figure(figsize=(12, 6))
plt.plot(future_dates, prophet_forecast['yhat'],
         label='Prophet', linestyle='--', marker='o')
plt.plot(future_dates, sarima_forecast,
         label='SARIMA', linestyle='--', marker='s')
plt.title('7-Day Accident Forecast Comparison')
plt.xlabel('Date')
plt.ylabel('Predicted Accidents')
plt.legend()
plt.grid(True)
plt.show()

# Print forecast comparison
print("\nDaily Forecasts:")
for date, p_pred, s_pred in zip(future_dates,
                               prophet_forecast['yhat'],
                               sarima_forecast):
    print(f"{date.date()}: Prophet={p_pred:.1f}, SARIMA={s_pred:.1f}")
```

```
c:\Users\garet\Documents\GitHub\DT503\env\Lib\site-
packages\statsmodels\tsa\base\tsa_model.py:837: ValueWarning: No supported index
```

```
is available. Prediction results will be given with an integer index beginning
at `start`.
  return get_prediction_index(
c:\Users\garet\Documents\GitHub\DT503\env\Lib\site-
packages\statsmodels\tsa\base\tsa_model.py:837: FutureWarning: No supported
index is available. In the next version, calling this method in a model without
a supported index will result in an exception.
  return get_prediction_index(
```




```
Daily Forecasts:
2023-12-31: Prophet=4.0, SARIMA=6.4
2024-01-01: Prophet=5.3, SARIMA=7.1
2024-01-02: Prophet=5.8, SARIMA=5.8
2024-01-03: Prophet=5.4, SARIMA=5.4
2024-01-04: Prophet=5.9, SARIMA=7.2
2024-01-05: Prophet=6.3, SARIMA=6.3
2024-01-06: Prophet=5.7, SARIMA=6.0
```

Predictions from SARIMA and Prophet provide a comparative view of future accident risks, forming the basis for actionable insights.

1.5 Model Evaluation

This section evaluates model accuracy using metrics like RMSE and MAE. We compare predictions against historical data and explore an ensemble approach to improve reliability.

Let's evaluate our models' performance using historical data:

```
[6]: def evaluate_models(analyser: TimeSeriesAnalyser,
                     test_data: pd.DataFrame) -> Dict:
        """Evaluate model performance using test data."""
        # Prepare actual values and ensure dates are sorted
        daily_actuals = test_data.groupby('date').size().sort_index()
        test_dates = daily_actuals.index

        print(f"Evaluation period: {test_dates.min()} to {test_dates.max()}")
        print(f"Number of test days: {len(test_dates)}")

        try:
            # Get Prophet predictions
            prophet_df = analyser.predict_prophet(test_dates)
            prophet_preds = pd.Series(
                prophet_df['yhat'].values,
                index=test_dates,
                name='Prophet'
            )

            # Get SARIMA predictions - adjust prediction length
            sarima_preds = analyser.sarima_results.predict(
                start=test_dates[0],
                end=test_dates[-1],
                dynamic=False  # Changed to False to match dates exactly
            )

            # Ensure predictions match actual dates exactly
            sarima_preds = sarima_preds[test_dates]

            # Convert to Series with matching index
            sarima_preds = pd.Series(
                sarima_preds,
                index=test_dates,
                name='SARIMA'
            )

            # Calculate ensemble predictions
            ensemble_preds = pd.Series(
                (prophet_preds + sarima_preds) / 2,
                index=test_dates,
                name='Ensemble'
            )

            # Verify alignments
            print(f"\nPrediction lengths:")
            print(f"Actuals: {len(daily_actuals)}")
            print(f"Prophet: {len(prophet_preds)}")
```

```
        print(f"SARIMA: {len(sarima_preds)}")
        print(f"Ensemble: {len(ensemble_preds)}")

        # Verify all indices match
        assert all(len(x) == len(daily_actuals) for x in [prophet_preds,␣
↪sarima_preds, ensemble_preds])
        assert all(x.index.equals(daily_actuals.index) for x in [prophet_preds,␣
↪sarima_preds, ensemble_preds])

        # Calculate metrics
        metrics = {
            'Prophet': {
                'RMSE': np.sqrt(mean_squared_error(daily_actuals,␣
↪prophet_preds)),
                'MAE': mean_absolute_error(daily_actuals, prophet_preds)
            },
            'SARIMA': {
                'RMSE': np.sqrt(mean_squared_error(daily_actuals,␣
↪sarima_preds)),
                'MAE': mean_absolute_error(daily_actuals, sarima_preds)
            },
            'Ensemble': {
                'RMSE': np.sqrt(mean_squared_error(daily_actuals,␣
↪ensemble_preds)),
                'MAE': mean_absolute_error(daily_actuals, ensemble_preds)
            }
        }

        return metrics, daily_actuals, prophet_preds, sarima_preds,␣
↪ensemble_preds

    except Exception as e:
        print(f"Error during evaluation: {str(e)}")
        print(f"Test dates shape: {test_dates.shape}")
        print(f"SARIMA predictions shape: {sarima_preds.shape if 'sarima_preds'␣
↪in locals() else 'Not created'}")
        raise

# Split data for evaluation
cutoff_date = '2023-12-01'
train_mask = data['date'] < cutoff_date
train_data = data[train_mask].copy()
test_data = data[~train_mask].copy()

print(f"Training period: {train_data['date'].min()} to {train_data['date'].
↪max()}")
```

```python
print(f"Testing period: {test_data['date'].min()} to {test_data['date'].max()}")

# Train models on training data
print("\nTraining models...")
evaluation_analyser = TimeSeriesAnalyser()
evaluation_analyser.fit_prophet(train_data)
evaluation_analyser.fit_sarima(train_data)
print("Training complete!")

# Evaluate models
metrics, actuals, prophet_preds, sarima_preds, ensemble_preds = evaluate_models(
    evaluation_analyser, test_data
)

# Print metrics
print("\nModel Performance Metrics:")
print("\nRoot Mean Square Error (RMSE):")
for model, metrics_dict in metrics.items():
    print(f"{model}: {metrics_dict['RMSE']:.2f}")

print("\nMean Absolute Error (MAE):")
for model, metrics_dict in metrics.items():
    print(f"{model}: {metrics_dict['MAE']:.2f}")
```

```
Training period: 2023-01-02 00:00:00 to 2023-11-30 00:00:00
Testing period: 2023-12-01 00:00:00 to 2023-12-31 00:00:00

Training models…
```

```
12:03:19 - cmdstanpy - INFO - Chain [1] start processing
12:03:19 - cmdstanpy - INFO - Chain [1] done processing
c:\Users\garet\Documents\GitHub\DT503\env\Lib\site-
packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: No frequency
information was provided, so inferred frequency D will be used.
  self._init_dates(dates, freq)
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packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: No frequency
information was provided, so inferred frequency D will be used.
  self._init_dates(dates, freq)
c:\Users\garet\Documents\GitHub\DT503\env\Lib\site-
packages\statsmodels\tsa\statespace\sarimax.py:978: UserWarning: Non-invertible
starting MA parameters found. Using zeros as starting parameters.
  warn('Non-invertible starting MA parameters found.'
```

```
Training complete!
Evaluation period: 2023-12-01 00:00:00 to 2023-12-31 00:00:00
Number of test days: 30

Prediction lengths:
```

```
Actuals: 30
Prophet: 30
SARIMA: 30
Ensemble: 30

Model Performance Metrics:

Root Mean Square Error (RMSE):
Prophet: 4.76
SARIMA: 3.57
Ensemble: 4.01

Mean Absolute Error (MAE):
Prophet: 3.71
SARIMA: 2.73
Ensemble: 3.06
```

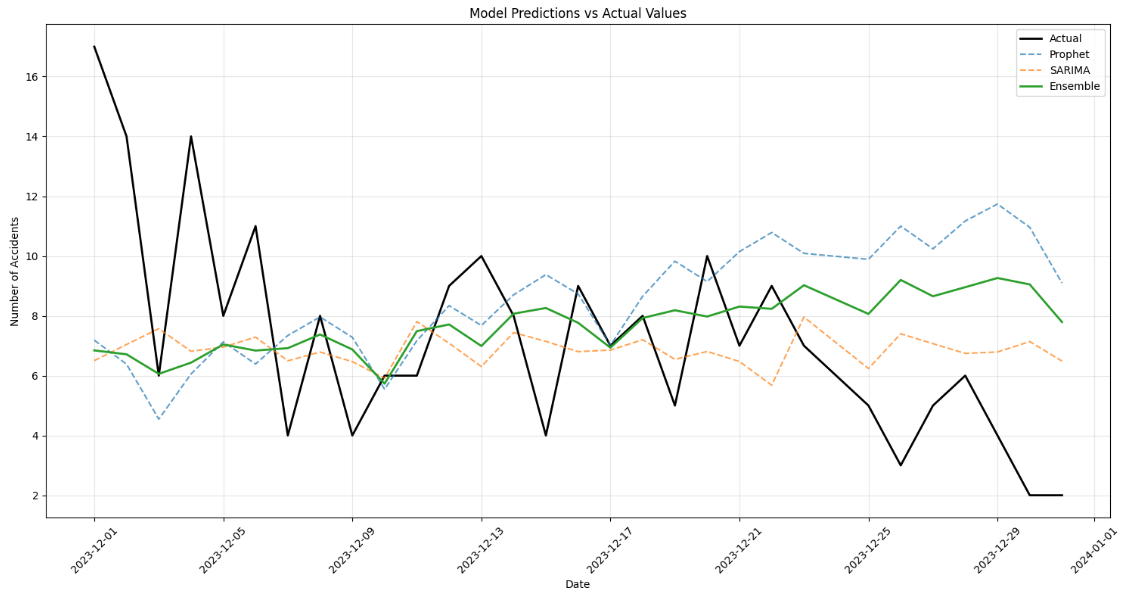
Let's visualise the evaluation results:

[7]:
```
# Create visualization
plt.figure(figsize=(15, 8))

# Plot actual values
plt.plot(actuals.index, actuals,
         label='Actual', color='black', linewidth=2)

# Plot predictions
plt.plot(actuals.index, prophet_preds,
         label='Prophet', linestyle='--', alpha=0.7)
plt.plot(actuals.index, sarima_preds,
         label='SARIMA', linestyle='--', alpha=0.7)
plt.plot(actuals.index, ensemble_preds,
         label='Ensemble', linewidth=2)

plt.title('Model Predictions vs Actual Values')
plt.xlabel('Date')
plt.ylabel('Number of Accidents')
plt.legend()
plt.grid(True, alpha=0.3)
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



We've assessed model performance and identified strengths and weaknesses, providing a robust framework for risk prediction.

1.6 Exporting the model

We can save the trained models to files for reuse, enabling integration with external tools like Power BI for dynamic accident risk forecasting.

[9]:
```python
import pickle

# Save SARIMA model
with open('sarima_model.pkl', 'wb') as sarima_file:
    pickle.dump(sarima_forecast, sarima_file)

# Save Prophet model
with open('prophet_model.pkl', 'wb') as prophet_file:
    pickle.dump(prophet_forecast, prophet_file)

print("Models saved successfully!")
```

```
Models saved successfully!
```

The models are exported, ready for deployment in Power BI or other systems to deliver real-time risk predictions.

1.7 Summary

In this tutorial, we explored the end-to-end process of traffic accident risk prediction using advanced time series analysis techniques. Starting with data preparation, we analysed seasonal patterns to uncover critical trends in accident occurrences across different timeframes.

We evaluated model performance using metrics like RMSE and MAE, comparing their accuracy and combining their strengths through an ensemble approach. The trained models were then exported, enabling seamless integration with tools like Power BI for real-time, dynamic forecasting.

We will be continuing on with this analysis in our next facilitated workshop, using the models we have built to predict and visualise the results in PowerBI.