Time Series Forecasting
with Machine Learning

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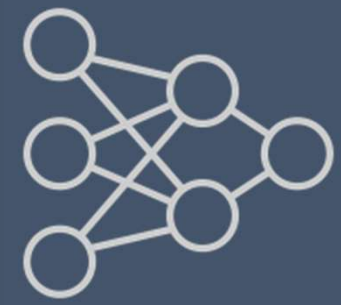
About me

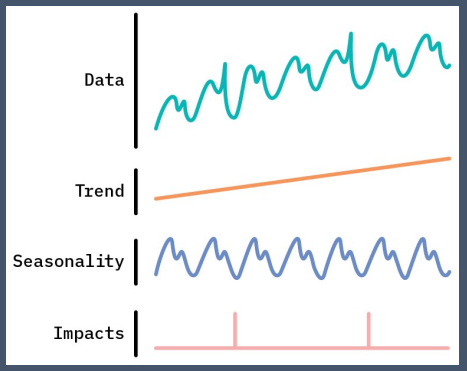
- 2nd Year PhD Student at the University of Bath
- AAPS CDT
- Electric Vehicle charging modelling

Overview

Machine Learning Tools

Forecasting Methods

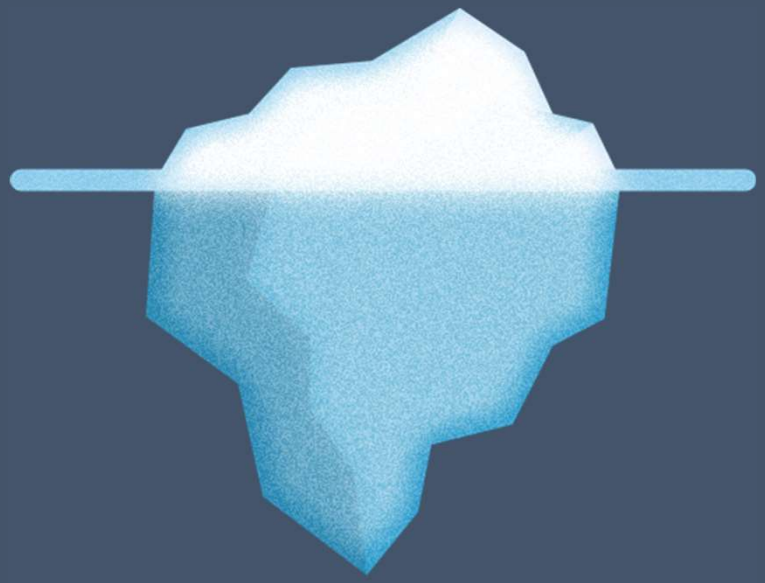




Overview

This workshop

Machine Learning and Time Series Forecasting



Overview

1. Introduction to Time Series Forecasting
2. Introduction to:
   - Python
   - TensorFlow
   - The Data
3. Neural Network Models
4. Structural Time Series Models

1. Introduction to
Time Series Forecasting

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What is Time Series Forecasting?

- Predict future values based on past observations.

Forecast Horizon?

Time Series Forecasting in Energy Systems

- We can use time series forecasting to predict **electrical load** and **PV generation** in mini-grids.
- Plan for peak demand
- Optimize system design (e.g. battery storage)
- Ensure reliable power supply
- Better renewable integration

Time Series Forecasting Techniques

- Time series forecasting techniques can be broadly divided into two categories:

1. **Statistical models**: simple patterns and trends.
2. **Machine learning models**: complex relationships.

Statistical Models for Time Series Forecasting

- Autoregressive Integrated Moving Average (ARIMA)
- Seasonal Autoregressive Integrated Moving Average (SARIMA)
- Exponential Smoothing (ETS)
- **Structural Time Series (STS)**

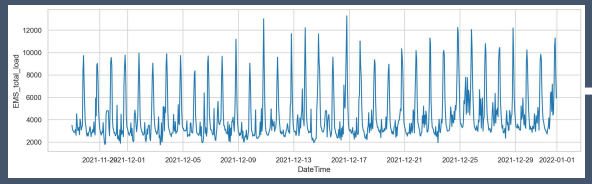
Machine Learning Models for Time Series Forecasting

- **Neural Networks (NN)**
- Random Forest (RF)
- Gradient Boosting (GB)

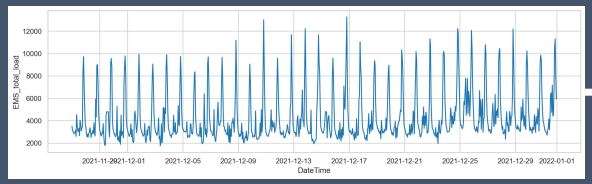
What do we want to Forecast?

Historical Data

Electrical Load



PV Generation



How can we learn from the data?

Model

Forecasts

Next Hour

Next 24 hours

Next Week

2. Introduction to
Python, TensorFlow and the Data

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Python 

- Python is a **high-level** programming language.
- Widely used for scientific computing, data analysis, machine learning and web development.
- **Simple** and easy to learn
- **Cross-platform**: can run on Windows, Mac and Linux
- **Open Source**

Installing Python with Anaconda

- Anaconda is a popular Python distribution for scientific computing.
- Includes Python, conda package manager, and many pre-installed packages.
- Download and install Anaconda from the official website.
- Follow the installation instructions for your operating system.

Creating Conda Environments

- Conda environments allow you to create isolated environments with **specific package versions**.
- Useful for **managing dependencies** and avoiding conflicts between packages.
- Create a new conda environment with the command: `conda create --name env_name`.
- Activate the environment with: `conda activate env_name`
- Deactivate the environment with: `conda deactivate`

Installing Packages (with Conda)

- Conda package manager allows you to easily install packages in your conda environment.
- Install a package with the command: `conda install package_name`.
- Specify a specific version of the package with: `conda install package_name=version`.
- Update a package with: `conda update package_name`.
- Remove a package with: `conda remove package_name`.

Installing Packages (with pip)

- pip is another popular package manager for Python.
- Can be used to install packages not available in conda.
- Install a package with the command: `pip install package_name`.
- Specify a specific version of the package with: `pip install package_name==version`.
- Update a package with: `pip install --upgrade package_name`.
- Remove a package with: `pip uninstall package_name`.

TensorFlow 

- TensorFlow is a popular open-source library for **machine learning** and **deep learning**.
- Developed by Google, it allows developers to build and train **neural networks**.
- Widely used for image recognition, natural language processing, and time series forecasting.

TensorFlow Probability

- TensorFlow Probability is an extension of TensorFlow for **probabilistic programming**.
- Allows developers to build and train models that incorporate **uncertainty**.
- Widely used for Bayesian modelling, time series analysis, and generative models

Jupyter Notebooks

- Jupyter Notebooks are an **interactive computing environment** that allows developers to create and share code.
- Provides a web-based interface for creating and editing notebooks.
- Allows developers to combine code, text, and visualizations in a single document.

Advantages of Jupyter Notebooks

- Interactive computing: allows developers to explore data and test code in real-time.
- Code sharing: allows developers to share code and analysis with others.
- Reproducibility: allows developers to reproduce analyses and experiments easily.

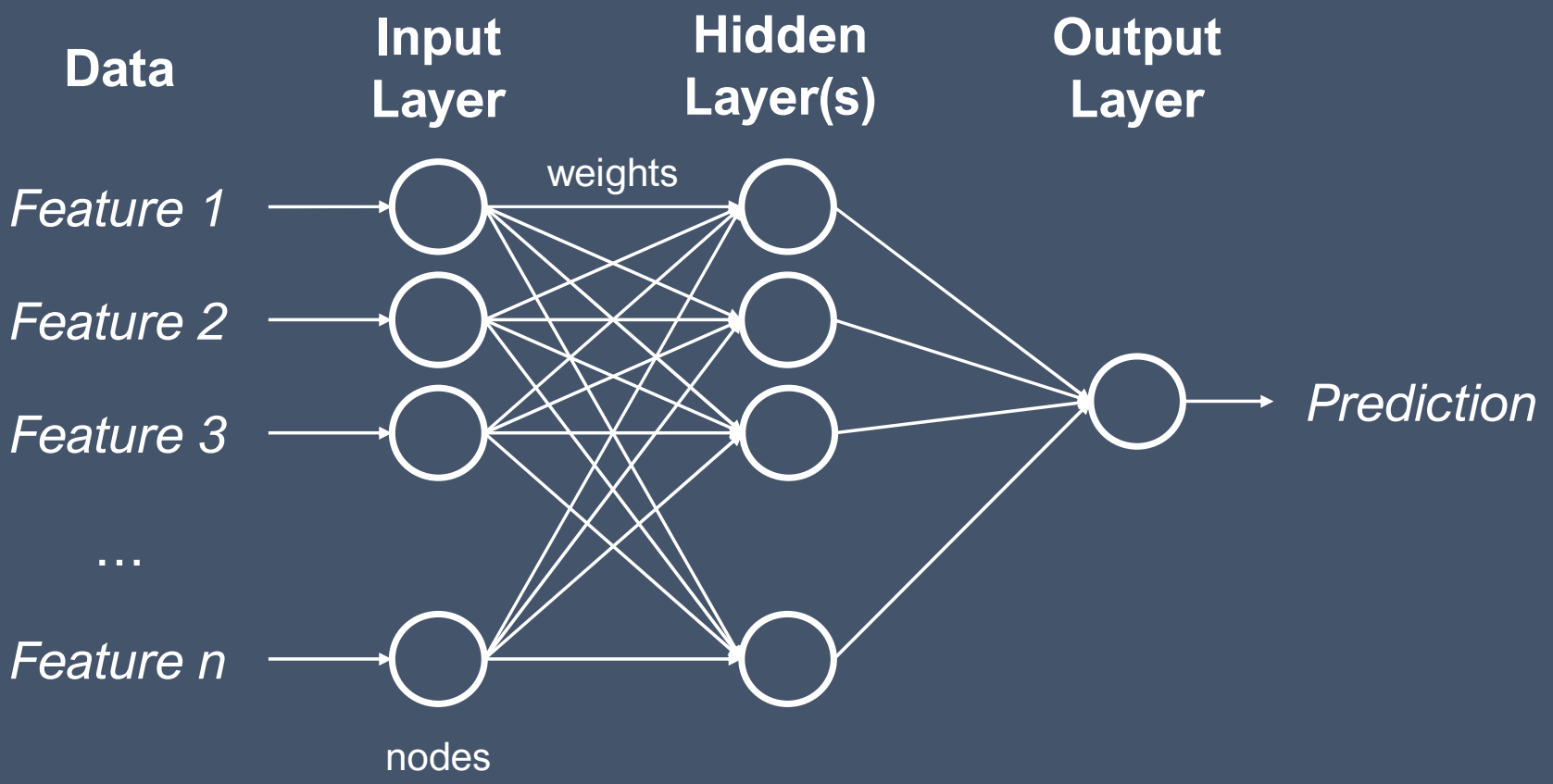
Jupyter Notebook Text Editors

- Jupyter Notebooks can be edited using a text editor or integrated development environment (IDE).
- Some of the popular text editors for Jupyter Notebooks include:
  - JupyterLab 

  - VS Code 
  - Atom 

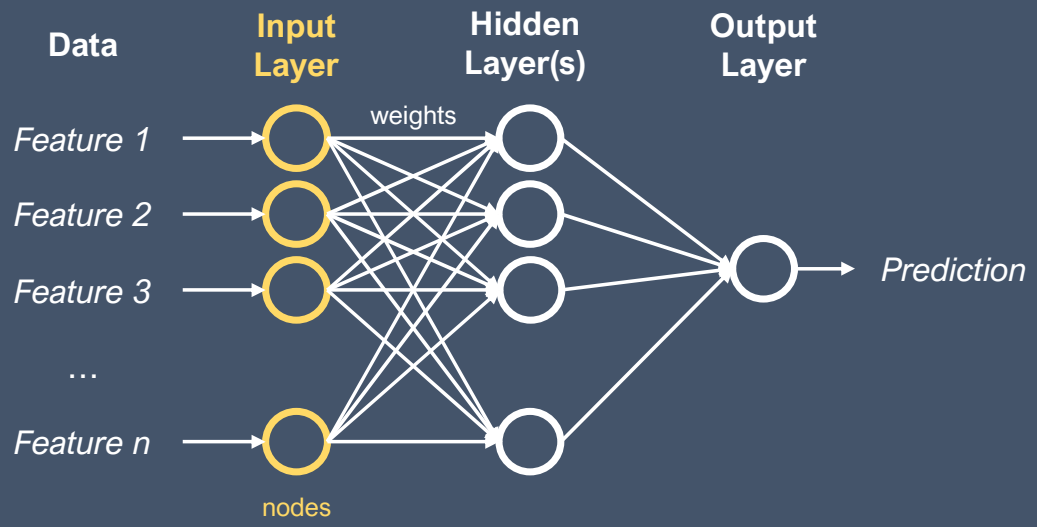
3. Neural Network Models

What are Neural Networks?



What are Neural Networks?

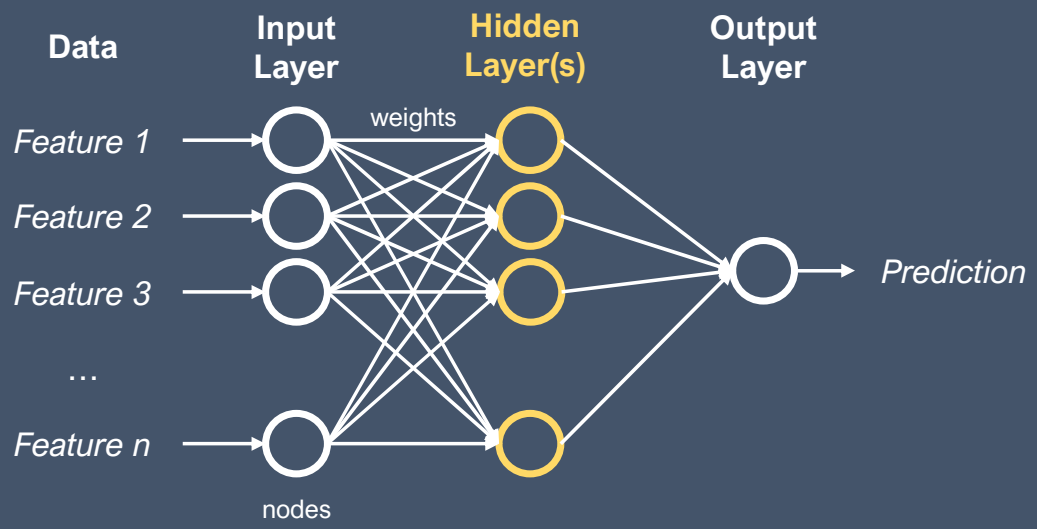
Input Layer



- The input layer is the first layer in the network and receives the input data.
- Each neuron in the input layer represents one feature of the input data.
- The input layer neurons simply pass the input data to the neurons in the first hidden layer.

What are Neural Networks?

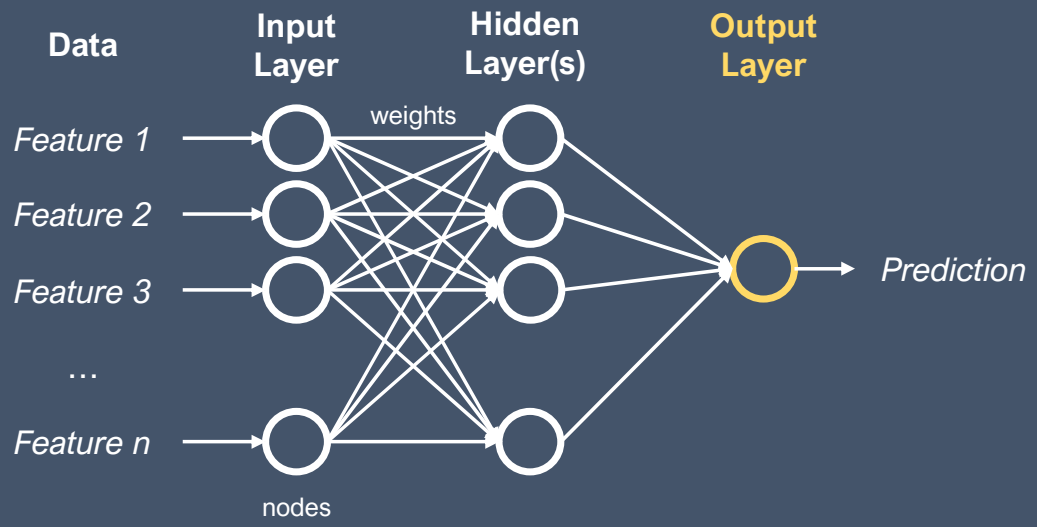
Hidden Layer(s)



- The hidden layers are located between the input and output layers and perform intermediate computations.
- Each neuron in a hidden layer receives inputs from all the neurons in the previous layer and produces an output signal.
- The outputs from the neurons in a hidden layer are then used as inputs to the neurons in the next layer.

What are Neural Networks?

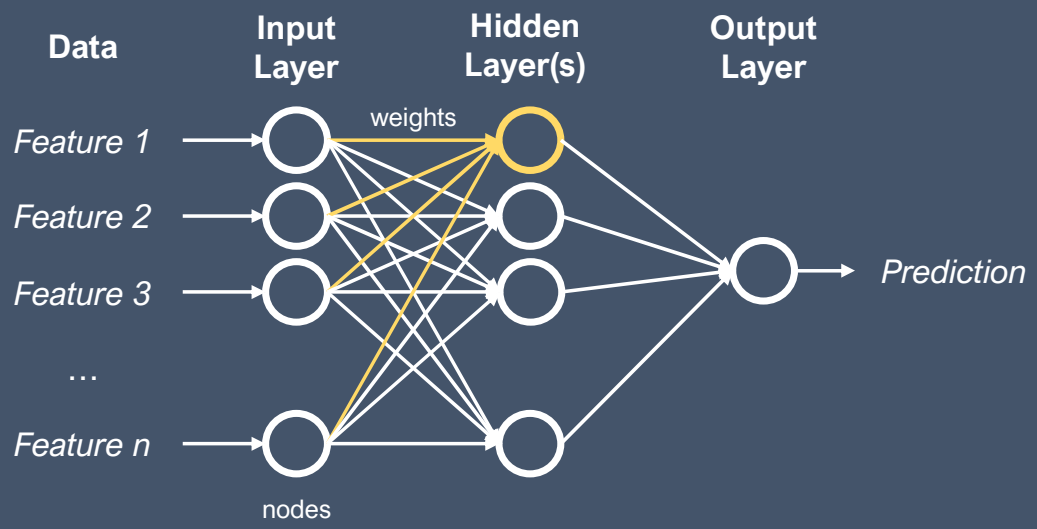
Output Layer



- The output layer is the last layer in the network and produces the network's predictions.
- The number of neurons in the output layer depends on the type of problem being solved.
- For example, in a binary classification problem, there would be one output neuron that produces a binary classification (0 or 1) for each input

What are Neural Networks?

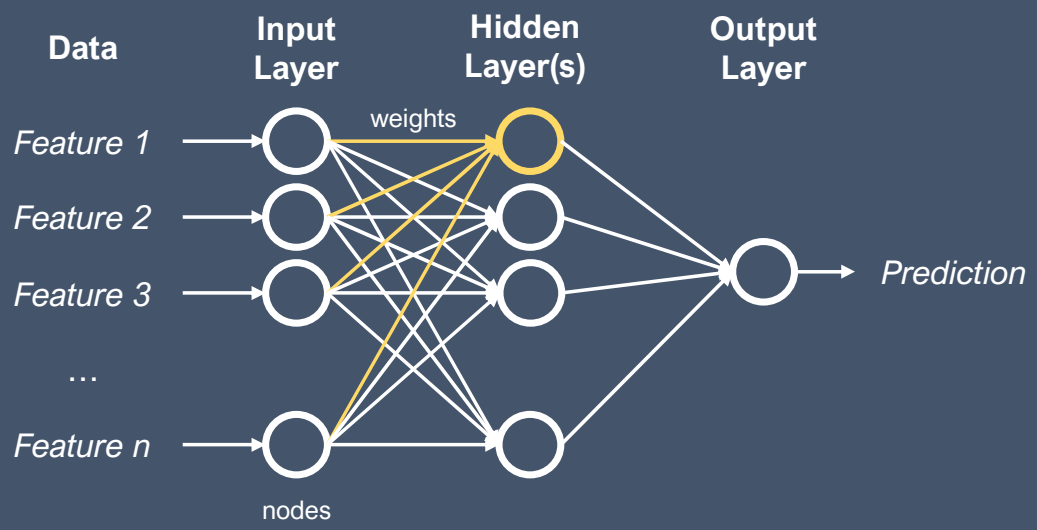
Activation Functions

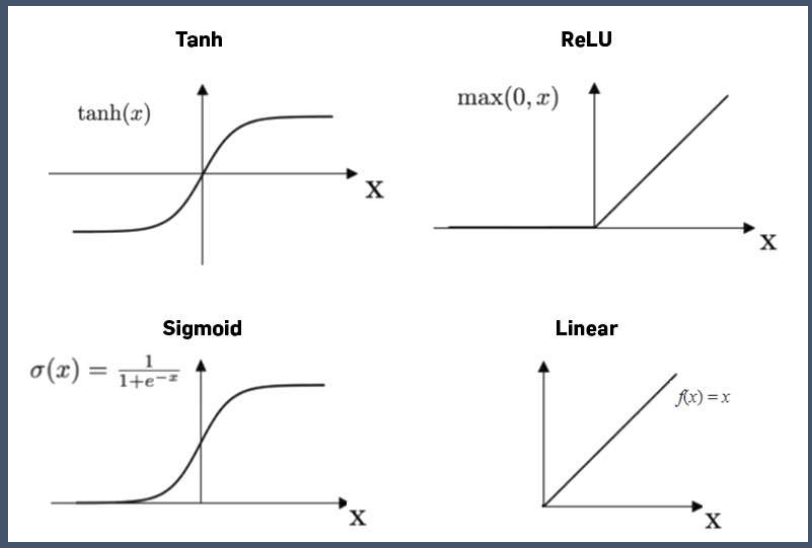


- Neurons typically use an activation function to produce an output signal.
- The activation function applies a non-linear transformation to the weighted sum of the inputs to the neuron.
- Common activation functions include the sigmoid function, ReLU function, and hyperbolic tangent function.

What are Neural Networks?

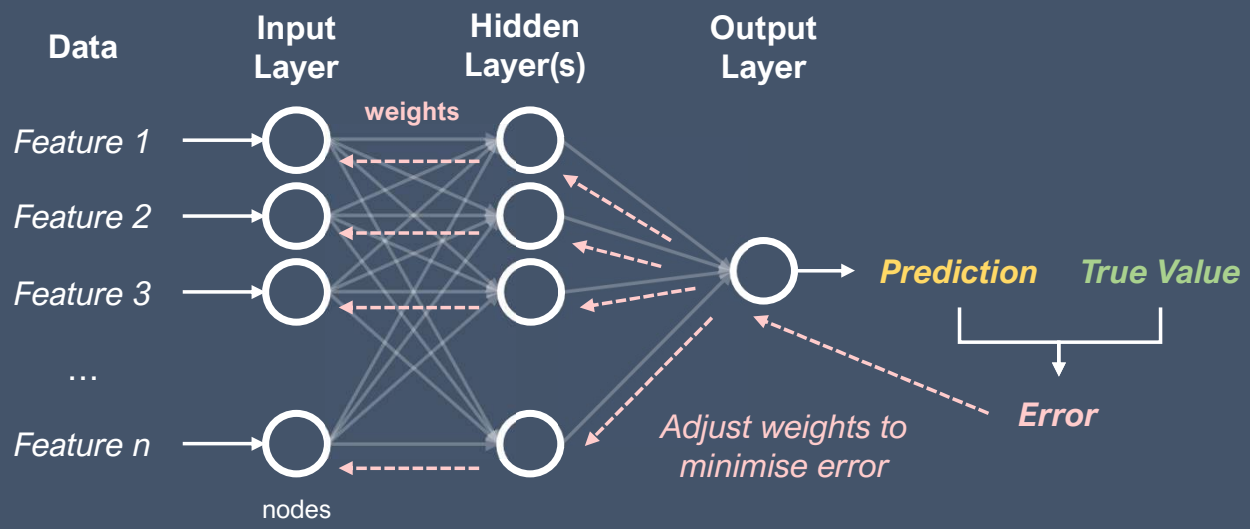
Activation Functions





Training Neural Networks

Backpropagation



- Neural networks are trained using **backpropagation**.
- Involves iteratively adjusting the weights of the network to minimise the error between the predicted outputs and true values.
- Backpropagation often uses optimization algorithms such as **gradient descent**

Data Pre-processing

- Before training a neural network, it is important to pre-process the data.
- Data pre-processing involves **cleaning** the data, handling **missing values**, and encoding **categorical variables**.
- Pre-processing can also include **scaling** or **normalizing** the data to ensure the neural network can learn effectively.

Data Pre-processing

DataFrame Pandas (pd)

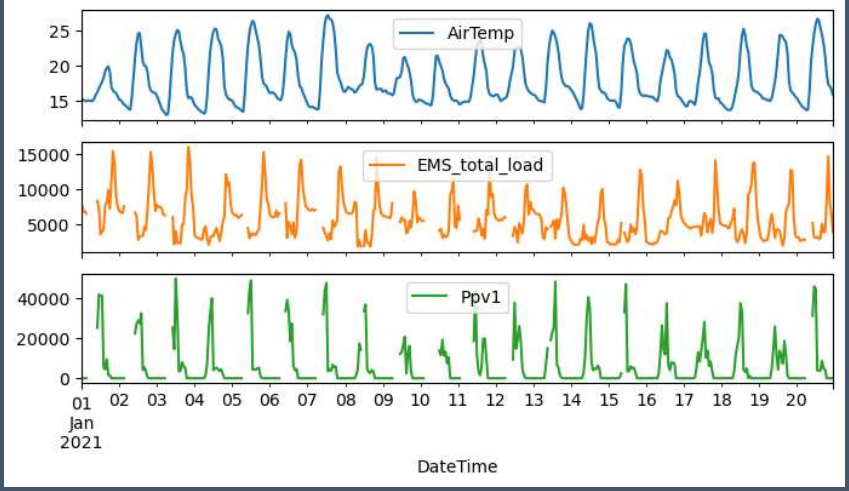
```
[75]
# Read Excel file as a DataFrame and skip row index 1 (the units)
df = pd.read_excel('../data/Combined EMS_Solcast data.xlsx', skiprows=[1])
```

```
[76]
df.head(5) # Displays the first 5 rows of the DataFrame
```

	Date	Time	AirTemp	Azimuth	CloudOpacity	DewpointTemp	Dhi	Dni	Ebh	Ghi	...	Fac	PrealL1	PrealL2	PrealL3	EMS_total_load	Pbat	SoC	Batv	Batc	InvBatV
0	2021-01-01	00:00:00	15.30	157.5	81.90	13.3	0.0	0.0	0.0	0.0	...	0.0	6400.0	1100.0	400.0	7900.0	9150.74	43.45	391.56	23.37	391.64
1	2021-01-01	00:10:00	15.25	162.5	82.25	13.3	0.0	0.0	0.0	0.0	...	0.0	6280.0	1030.0	400.0	7710.0	8503.12	42.72	391.49	21.72	391.55
2	2021-01-01	00:20:00	15.20	167.5	82.60	13.3	0.0	0.0	0.0	0.0	...	0.0	6160.0	950.0	400.0	7510.0	8153.45	42.11	391.43	20.83	391.52
3	2021-01-01	00:30:00	15.20	173.0	82.15	13.2	0.0	0.0	0.0	0.0	...	0.0	6070.0	860.0	400.0	7330.0	8406.17	41.22	391.35	21.48	391.42
4	2021-01-01	00:40:00	15.10	178.5	81.85	13.2	0.0	0.0	0.0	0.0	...	0.0	5870.0	810.0	400.0	7080.0	7922.02	40.26	391.21	20.25	391.32

5 rows × 35 columns

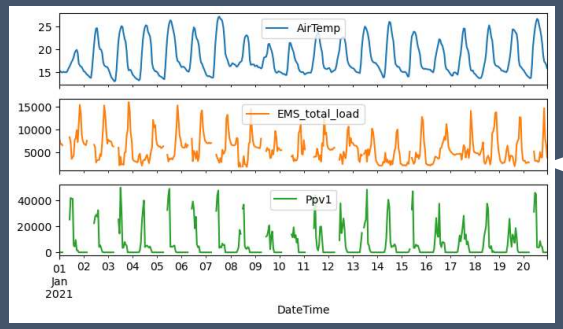
Missing Data



- Remove it (Not desirable with time series)
- Replace with mean/median
- Regression imputation
- K-nearest neighbour imputation
- Multivariate imputation by chained equation (MICE)

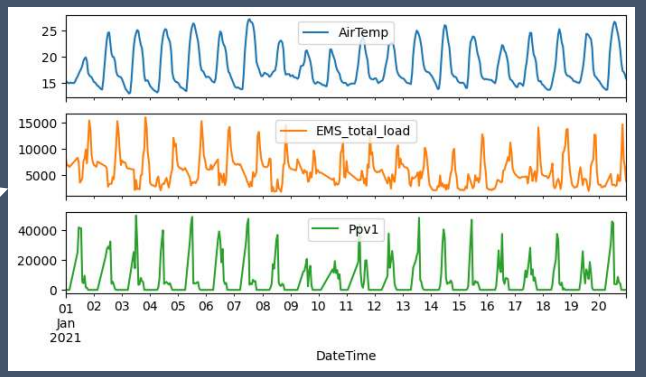
Missing Data

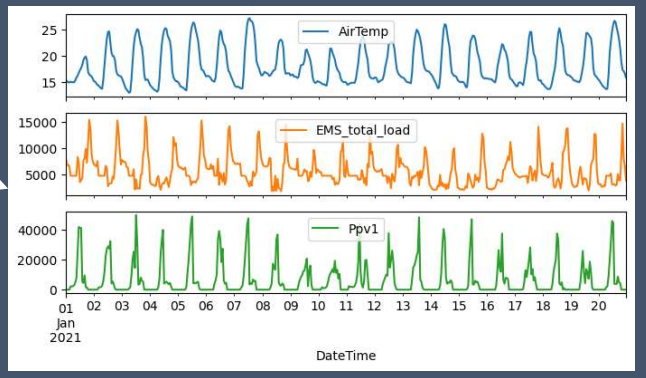
```
linear_interpolation = df[df.columns.drop(['Date', 'Time', 'DateTime'])].copy().interpolate(method='linear')
```



Linear Interpolation

Multivariate imputation by chained equation (MICE)



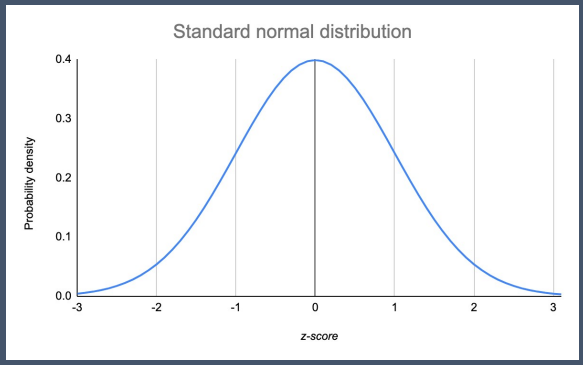



```python
# Imputing with MICE using sklearn
from sklearn.experimental import enable_iterative_imputer
from sklearn.impute import IterativeImputer
from sklearn import linear_model

# Define MICE Imputer and fill missing values
mice_imputer = IterativeImputer(estimator=linear_model.BayesianRidge(), n_nearest_features=None, imputation_order='ascending')

df_mice = pd.DataFrame(mice_imputer.fit_transform(df[df.columns.drop(['Date', 'Time', 'DateTime'])].copy()),
                       columns = df[df.columns.drop(['Date', 'Time', 'DateTime'])].copy().columns)
```

Data Standardisation

- Transforms input data to have a mean of zero and a standard deviation of one.
- Ensures input features are on the same scale, which accelerates convergence.
- Improves accuracy and stability by reducing the impact of outliers in the input data.

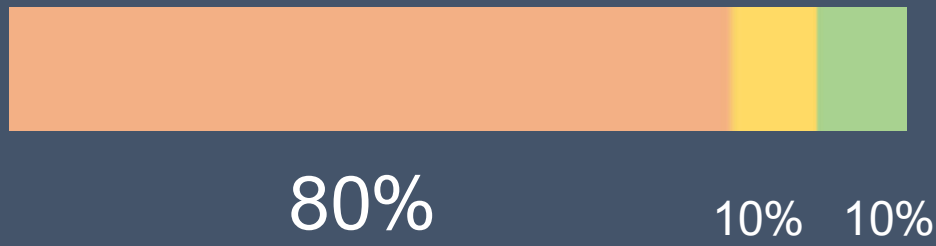
$$Z = \frac{x - \mu}{\sigma}$$




```
train_mean = train_df.mean()
train_std = train_df.std()

train_df = (train_df - train_mean) / train_std
val_df = (val_df - train_mean) / train_std
test_df = (test_df - train_mean) / train_std
```

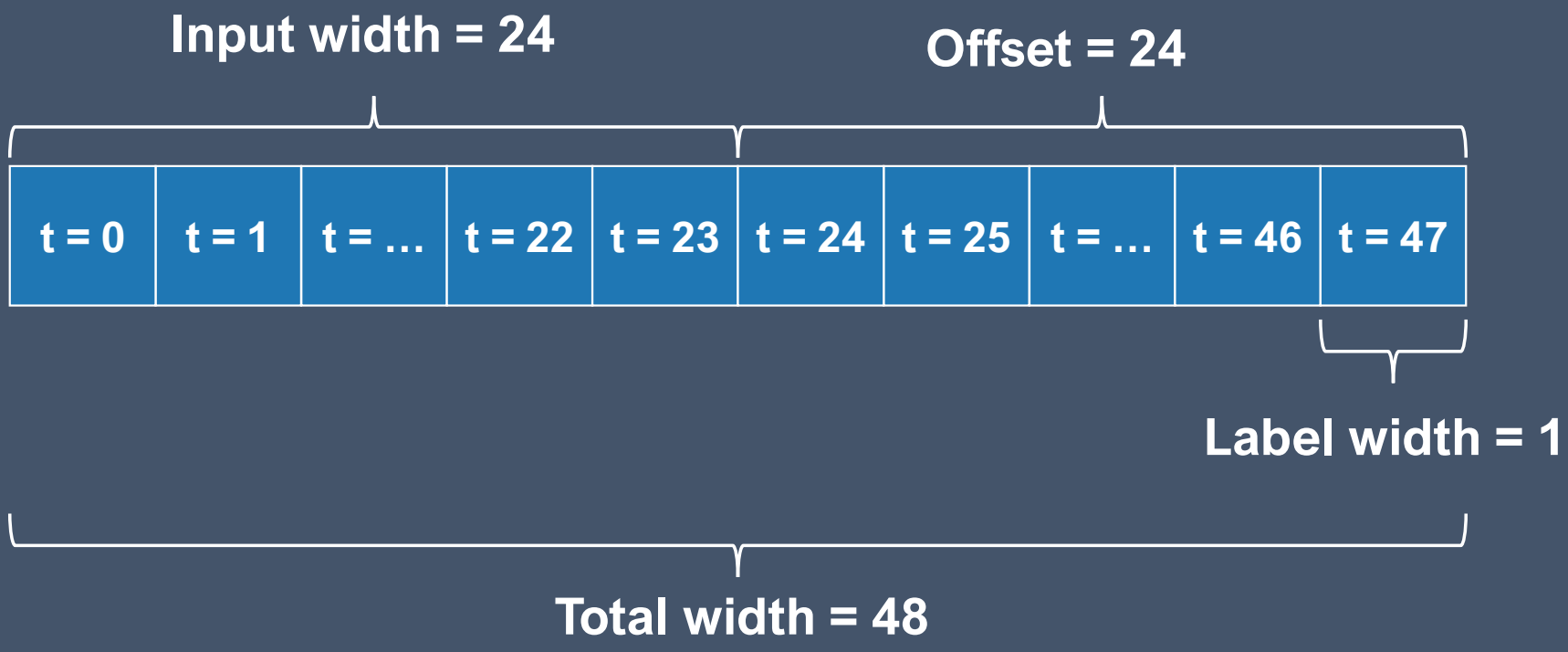
Test-Validation-Train Split

- **Training data**: train the neural network.
- **Validation data**: tune hyperparameters and prevent overfitting.
- **Test data**: evaluate the performance of the neural network on unseen data




```python
# Create dictionary containing the feature and the respective index
column_indices = {name: i for i, name in enumerate(df.columns)}

n = len(df)
train_df = df[0:int(n*0.8)] # Take first 80% of data
val_df = df[int(n*0.8):int(n*0.9)] # Take next 10% of data
test_df = df[int(n*0.9):] # Take last 10% of Data

num_features = df.shape[1] # Number of features (number of columns in df)
```

Data Windowing



Data Windowing

Time series data → `WindowGenerator` `split_window` `make_dataset` → Inputs Labels

Feature Selection

- Selecting a **subset of input variables** to include in the neural network.
- **Correlation analysis** or **feature importance ranking**.
- Feature selection can **improve the performance** of the neural network by **reducing overfitting** and **increasing interpretability**

Feature Selection

Electrical Load

- PrealL1
- PrealL2
- PrealL3
- EMS_total_load
- Day sin
- Day cos
- Week sin
- Week cos
- Year sin
- Year cos

Total Electrical Load

Sinusoidal time signals at daily, weekly and yearly frequency

PV Generation

Irradiance

- AirTemp
- CloudOpacity
- Dhi
- Dni
- Ebh
- Ghi
- GtiFixedTilt
- GtiTracking
- AlbedoDaily

PV Power

- Ppv1
- Day sin
- Day cos
- Week sin
- Week cos
- Year sin
- Year cos

Training Function

Loss function is mean squared error (MSE)

```
MAX_EPOCHS = 40

def compile_and_fit(model, window, patience=4):
  early_stopping = tf.keras.callbacks.EarlyStopping(monitor='val_loss',
                                                    patience=patience,
                                                    mode='min')

  model.compile(loss=tf.keras.losses.MeanSquaredError(),
                optimizer=tf.keras.optimizers.Adam(),
                metrics=[tf.keras.metrics.MeanAbsoluteError()])

  history = model.fit(window.train, epochs=MAX_EPOCHS,
                      validation_data=window.val,
                      callbacks=[early_stopping])
  return history
```

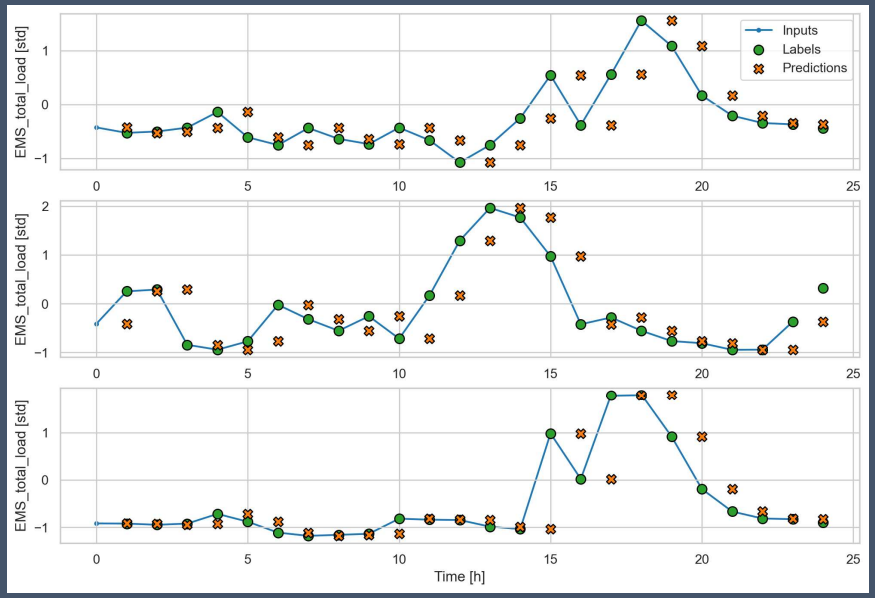
Stops training if validation loss doesn't decrease after 4 epochs

Single-step Output Models

Given some history,
Can we predict the value at the next hour?

Single-step Output Models

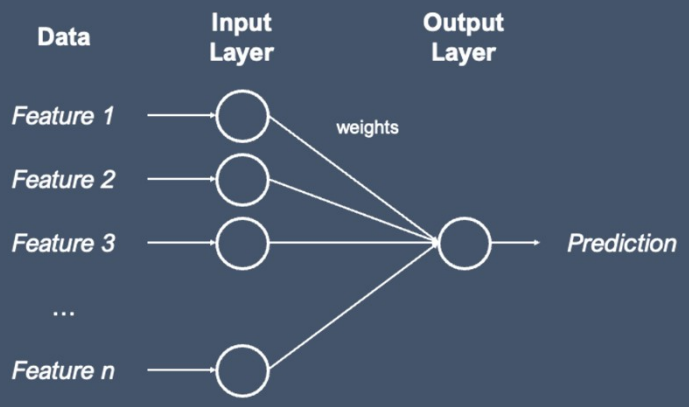
Baseline

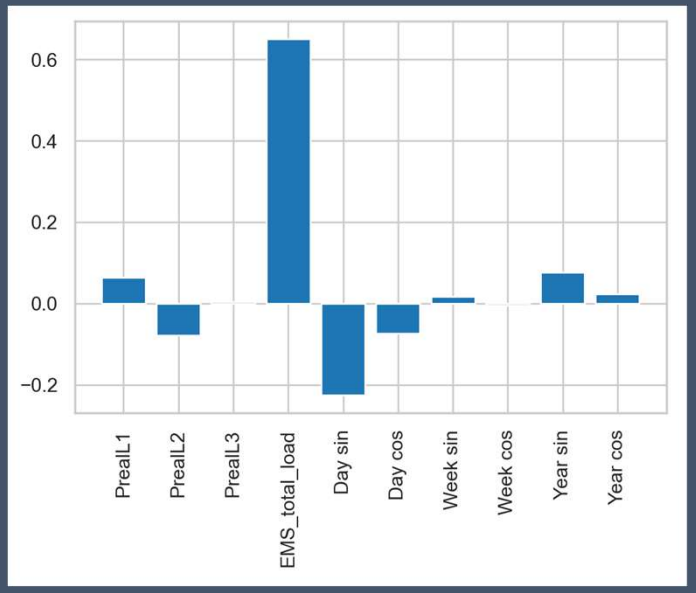


Single-step Output Models

Linear

```
linear = tf.keras.Sequential([
    tf.keras.layers.Dense(units=1)
])
```

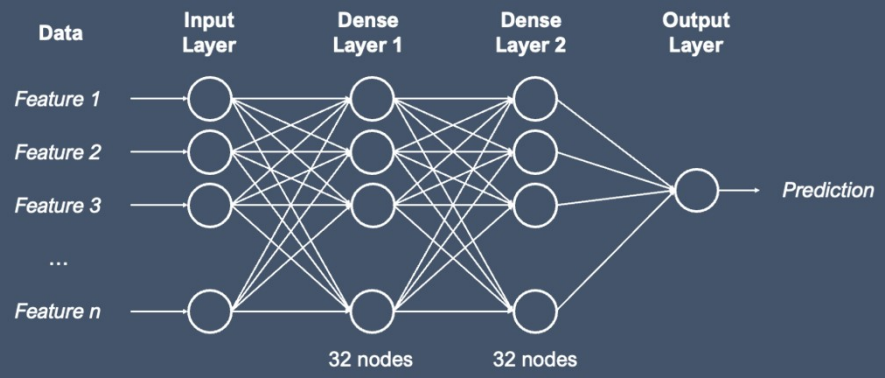




Single-step Output Models

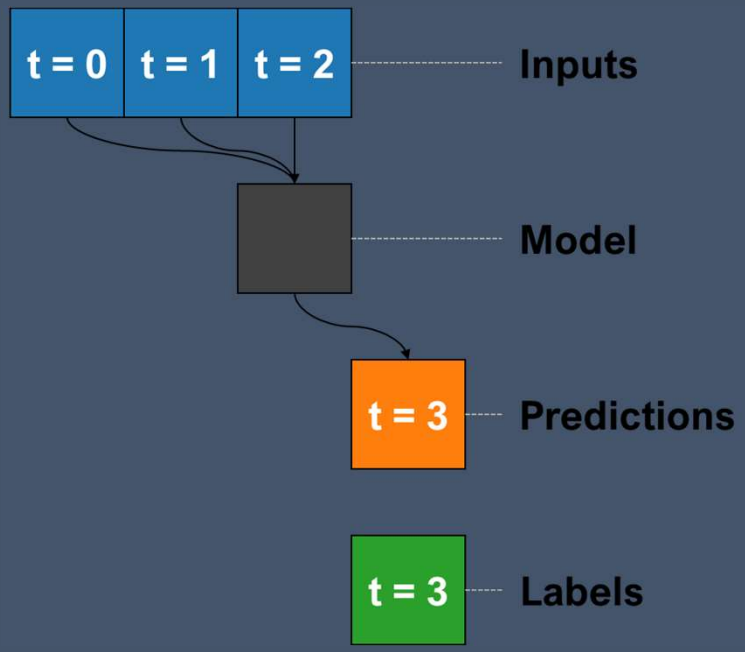
Dense

```
dense = tf.keras.Sequential([
    tf.keras.layers.Dense(units=32, activation='relu'),
    tf.keras.layers.Dense(units=32, activation='relu'),
    tf.keras.layers.Dense(units=1)
])

history = compile_and_fit(dense, single_step_window)

val_performance['Dense'] = dense.evaluate(single_step_window.val)
performance['Dense'] = dense.evaluate(single_step_window.test, verbose=0)
```



Single-step Output Models

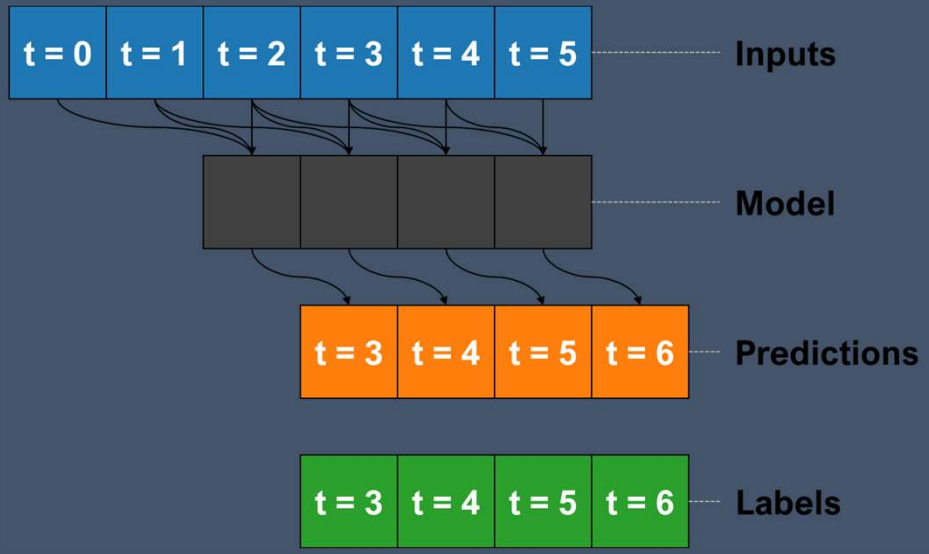
Multi-input Dense




```python
multi_step_dense = tf.keras.Sequential([
    # Shape: (time, features) => (time*features)
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(units=32, activation='relu'),
    tf.keras.layers.Dense(units=32, activation='relu'),
    tf.keras.layers.Dense(units=1),
    # Add back the time dimension.
    # Shape: (outputs) => (1, outputs)
    tf.keras.layers.Reshape([1, -1]),
])
```

Single-step Output Models

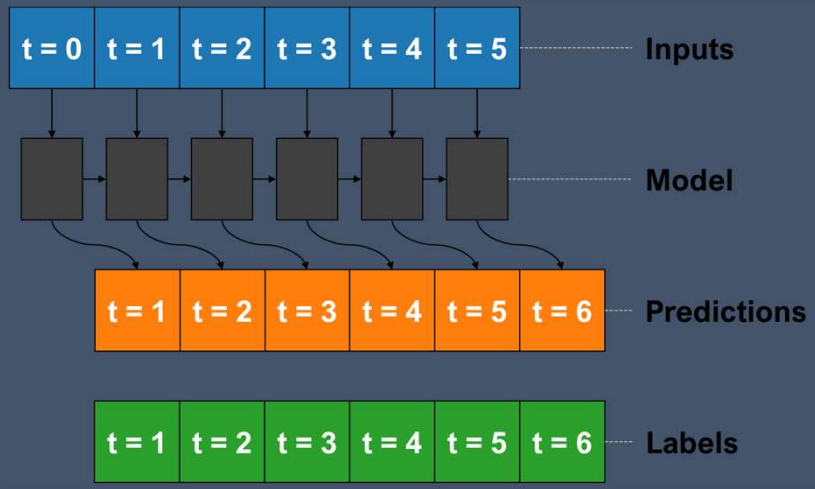
Convolutional Neural Network (CNN)




```
conv_model = tf.keras.Sequential([
    tf.keras.layers.Conv1D(filters=32,
                           kernel_size=(CONV_WIDTH,),
                           activation='relu'),
    tf.keras.layers.Dense(units=32, activation='relu'),
    tf.keras.layers.Dense(units=1),
])
```

Single-step Output Models

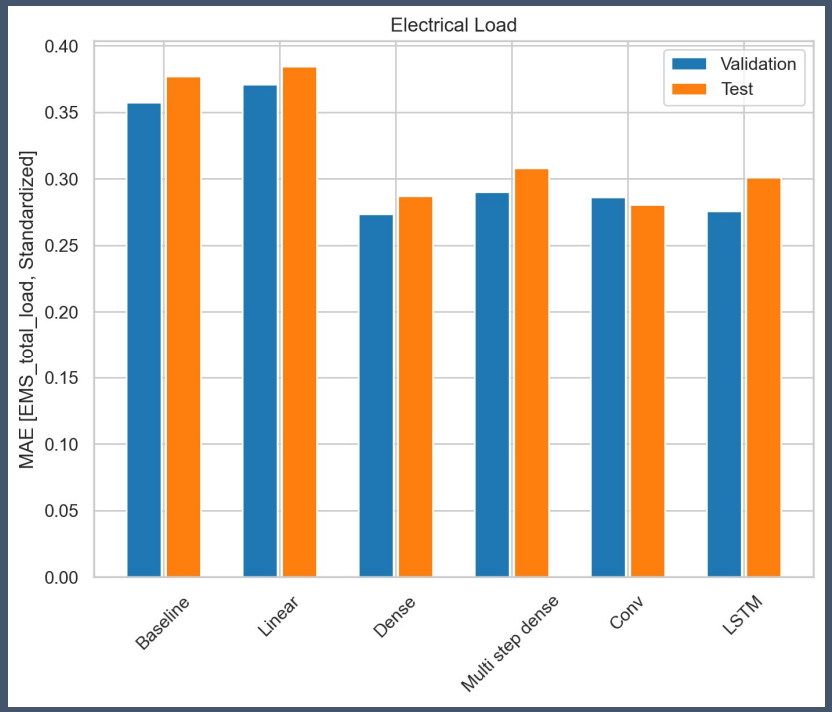
Long-Short Term Memory (LSTM)

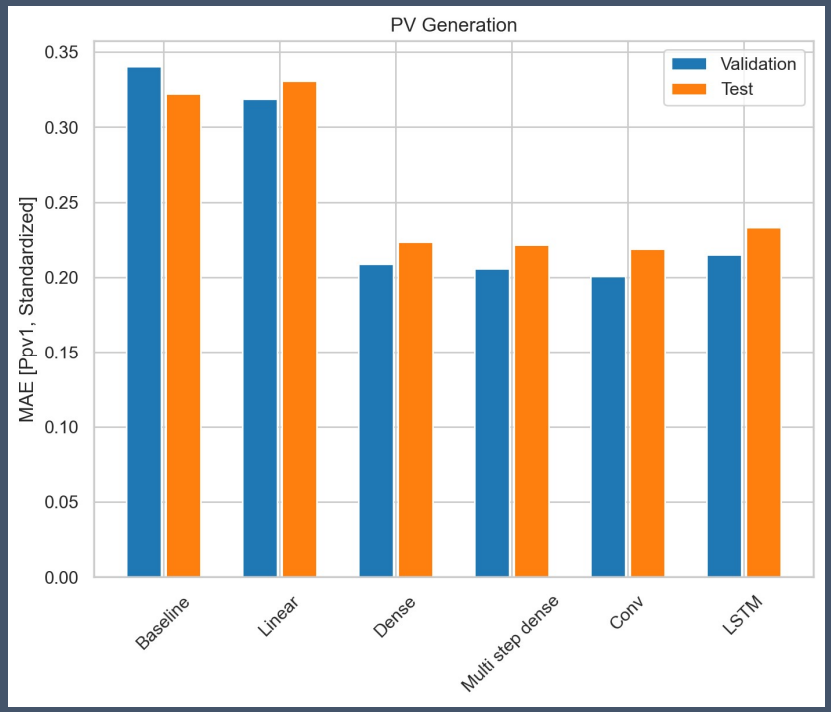



```
lstm_model = tf.keras.models.Sequential([
    # Shape [batch, time, features] => [batch, time, lstm_units]
    tf.keras.layers.LSTM(32, return_sequences=True),
    # Shape => [batch, time, features]
    tf.keras.layers.Dense(units=1)
])
```

Single-step Output Models

Performance Comparison



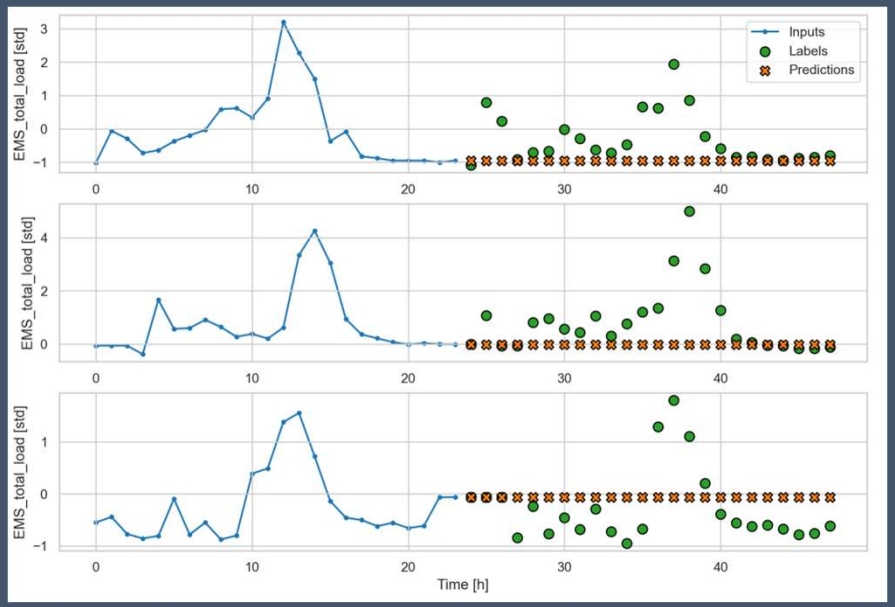


Multi-step Output Models

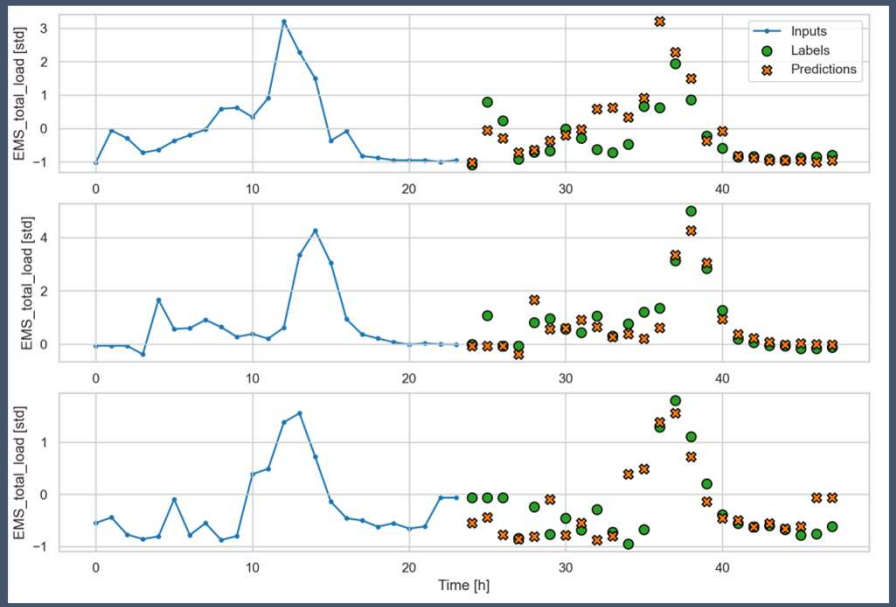
Given some history,
Can we predict the value at the next **24 hours**?

Multi-step Output Models

Baseline (Last)

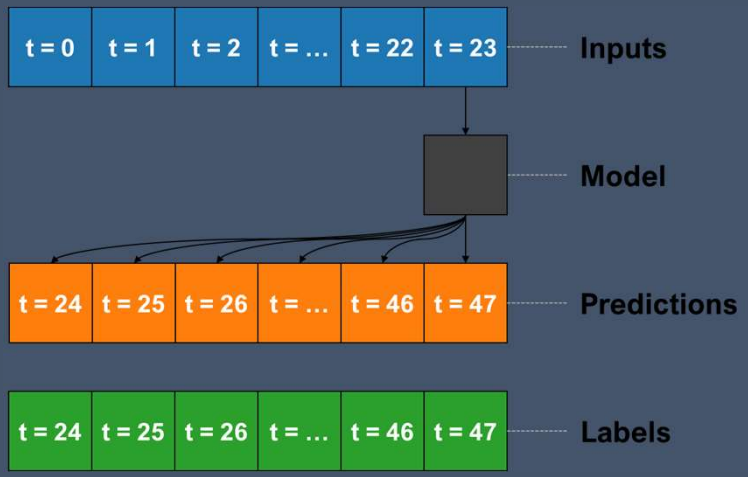


Baseline (Repeat)



Multi-step Output Models

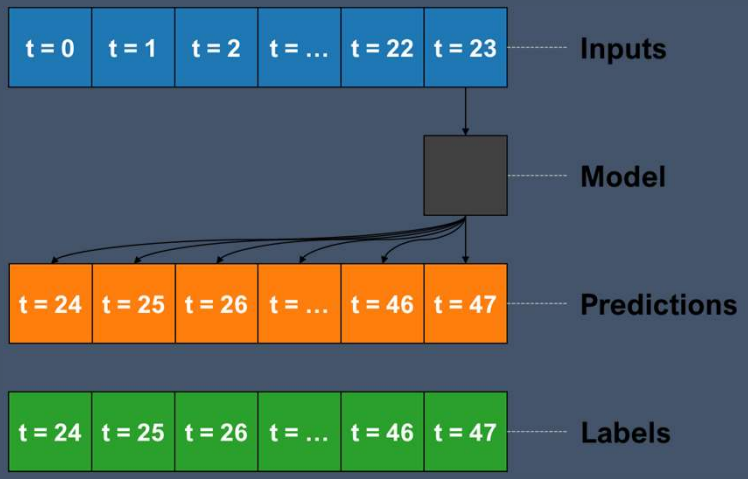
Multi-linear




```
multi_linear_model = tf.keras.Sequential([
    # Take the last time-step.
    # Shape [batch, time, features] => [batch, 1, features]
    tf.keras.layers.Lambda(lambda x: x[:, -1:, :]),
    # Shape => [batch, 1, out_steps*features]
    tf.keras.layers.Dense(OUT_STEPS,
                          kernel_initializer=tf.initializers.zeros()),
    # Shape => [batch, out_steps, features]
    # tf.keras.layers.Reshape([OUT_STEPS, num_features])
    tf.keras.layers.Reshape([OUT_STEPS, 1])
])
```

Multi-step Output Models

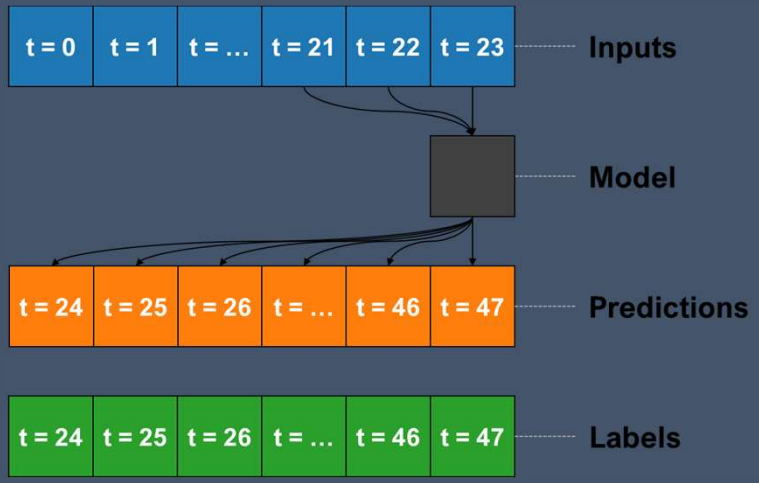
Multi-dense




```
multi_dense_model = tf.keras.Sequential([
    # Take the last time step.
    # Shape [batch, time, features] => [batch, 1, features]
    tf.keras.layers.Lambda(lambda x: x[:, -1:, :]),
    # Shape => [batch, 1, dense_units]
    tf.keras.layers.Dense(512, activation='relu'),
    # Shape => [batch, out_steps*features]
    tf.keras.layers.Dense(OUT_STEPS,
                          kernel_initializer=tf.initializers.zeros()),
    # Shape => [batch, out_steps, features]
    tf.keras.layers.Reshape([OUT_STEPS, 1])
])
```

Multi-step Output Models

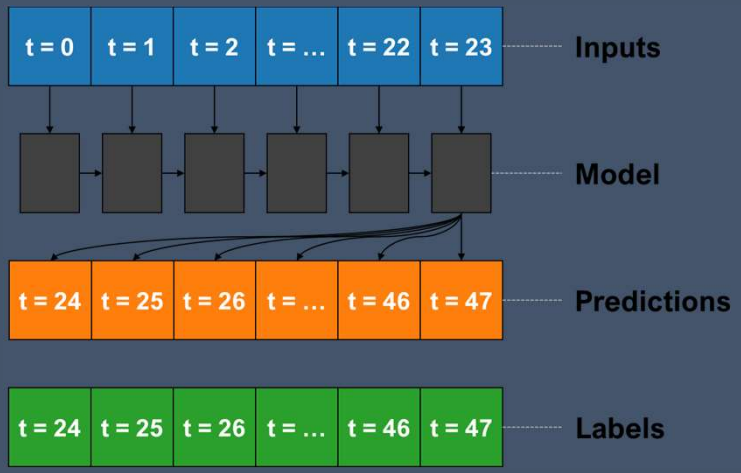
Multi-CNN




```
CONV_WIDTH = 3
multi_conv_model = tf.keras.Sequential([
    # Shape [batch, time, features] => [batch, CONV_WIDTH, features]
    tf.keras.layers.Lambda(lambda x: x[:, -CONV_WIDTH:, :]),
    # Shape => [batch, 1, conv_units]
    tf.keras.layers.Conv1D(256, activation='relu', kernel_size=(CONV_WIDTH)),
    # Shape => [batch, 1,  out_steps*features]
    tf.keras.layers.Dense(OUT_STEPS,
                          kernel_initializer=tf.initializers.zeros()),
    # Shape => [batch, out_steps, features]
    tf.keras.layers.Reshape([OUT_STEPS, 1])
])
```

Multi-step Output Models

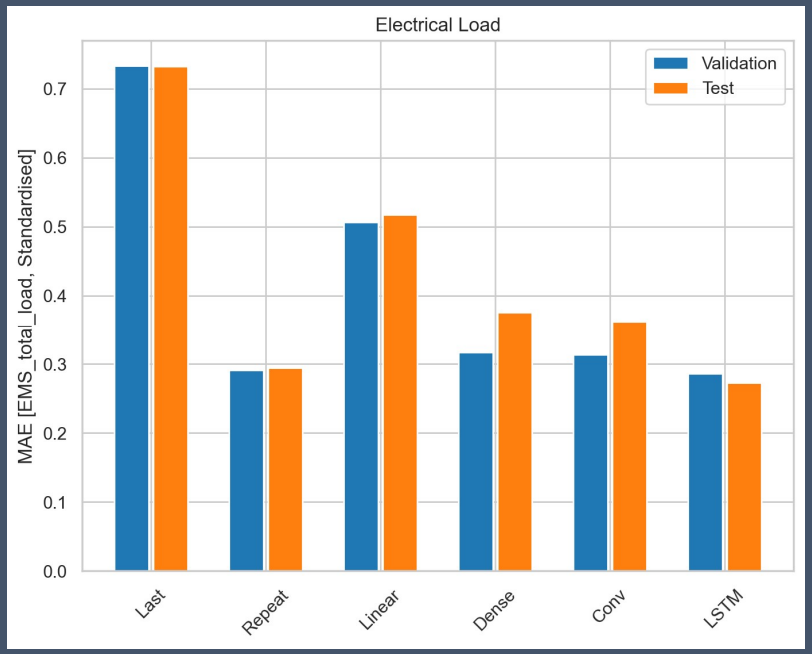
Multi-LSTM

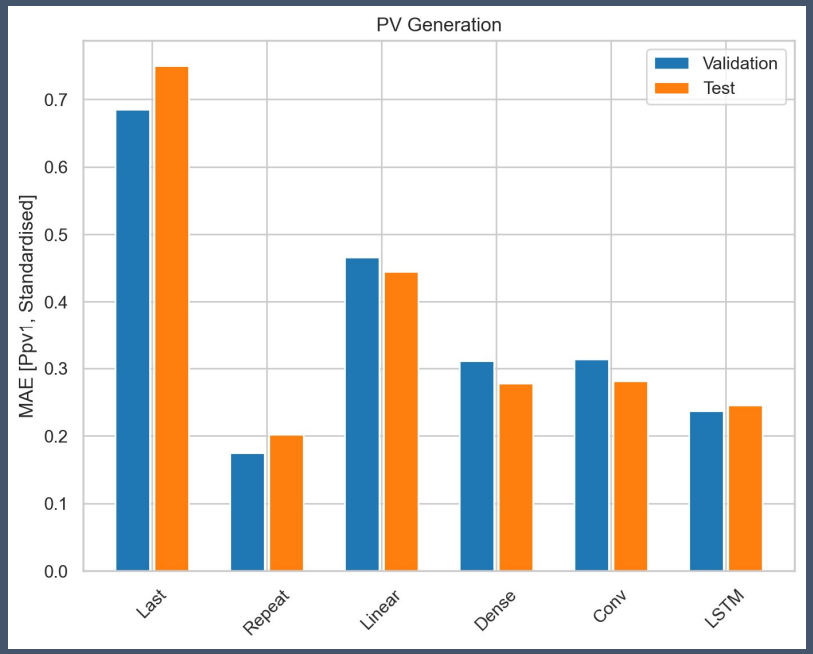



```
multi_lstm_model = tf.keras.Sequential([
    # Shape [batch, time, features] => [batch, lstm_units].
    # Adding more `lstm_units` just overfits more quickly.
    tf.keras.layers.LSTM(32, return_sequences=False),
    # Shape => [batch, out_steps*features].
    tf.keras.layers.Dense(OUT_STEPS,
                          kernel_initializer=tf.initializers.zeros()),
    # Shape => [batch, out_steps, features].
    tf.keras.layers.Reshape([OUT_STEPS, 1])
])
```

Multi-step Output Models

Performance Comparison

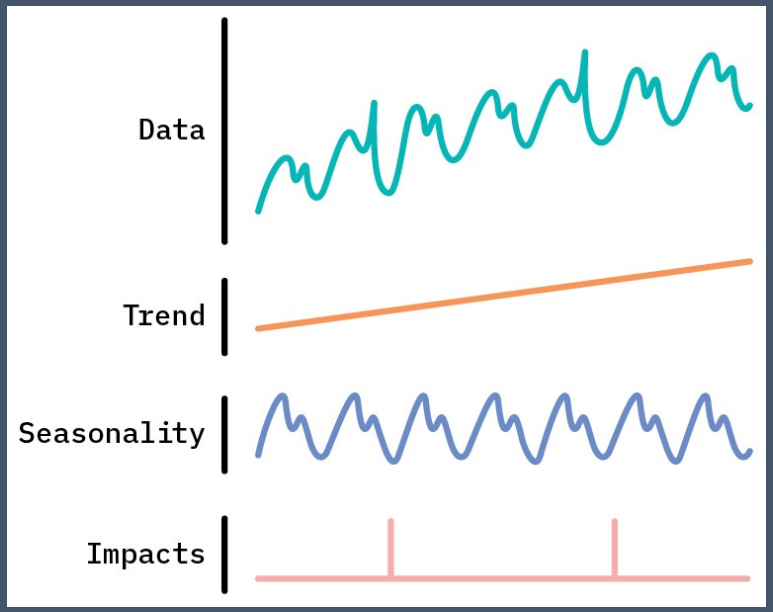




4. Structural Time Series Models

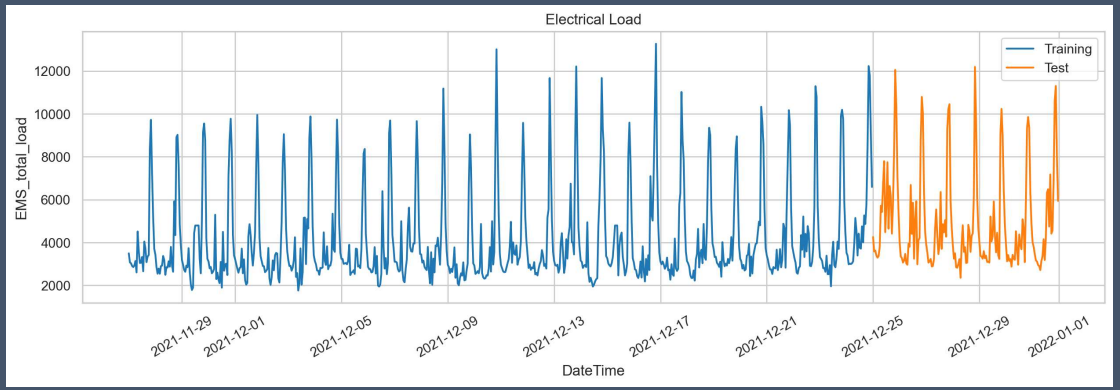
What is Structural Time Series?

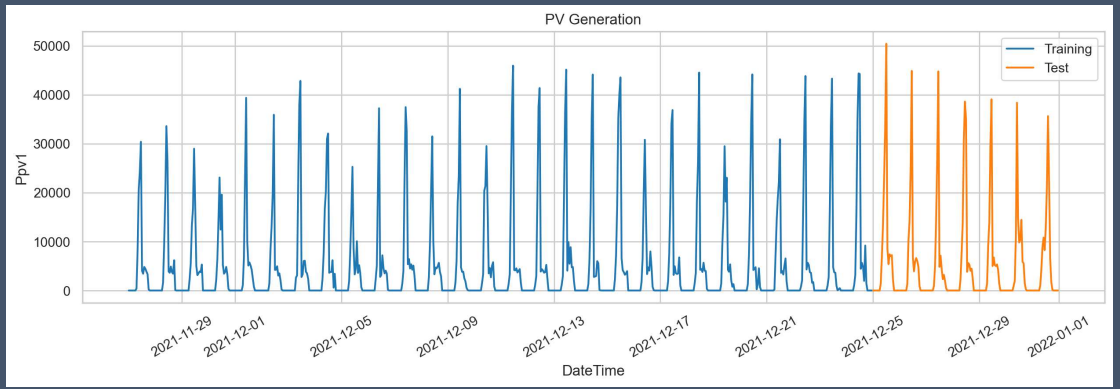
$$f(t) = f_1(t) + f_1(t) + \cdots f_n(t) + \varepsilon$$



- Time series is decomposed into functions that add together to reproduce the original series.
- Don't need a lot of data
- Interpretable
- Uncertainty Quantification

Data Selection





Model Components

Electrical Load

```
def build_model(observed_time_series):
  hour_of_day_effect = sts.Seasonal(
      num_seasons=24,
      observed_time_series=observed_time_series,
      name='hour_of_day_effect')
  day_of_week_effect = sts.Seasonal(
      num_seasons=7, num_steps_per_season=24,
      observed_time_series=observed_time_series,
      name='day_of_week_effect')
  temperature_effect = sts.LinearRegression(
      design_matrix=tf.reshape(temperature - np.mean(temperature),
                               (-1, 1)), name='temperature_effect')
  autoregressive = sts.Autoregressive(
      order=1,
      observed_time_series=observed_time_series,
      name='autoregressive')
  model = sts.Sum([hour_of_day_effect,
                   day_of_week_effect,
                   temperature_effect,
                   autoregressive],
                   observed_time_series=observed_time_series)
  return model
```

PV Generation

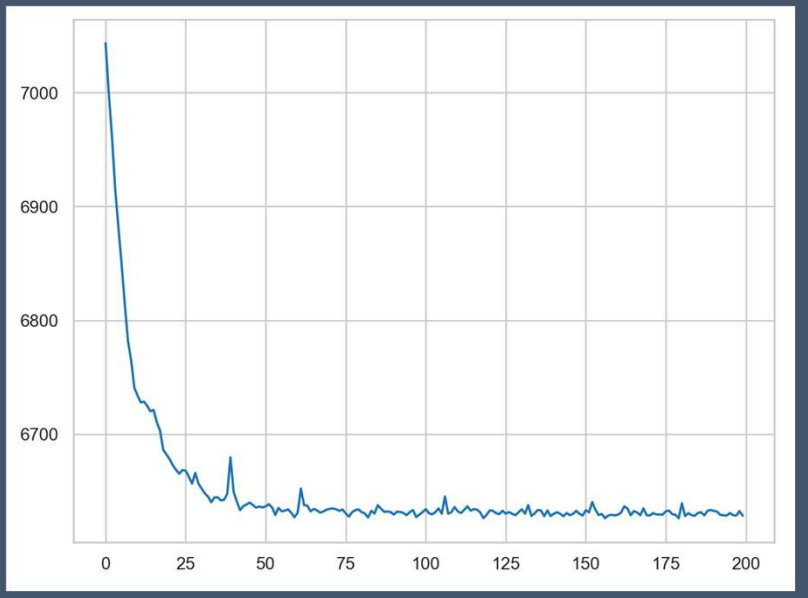
```
def build_model(observed_time_series):
  hour_of_day_effect = sts.Seasonal(
      num_seasons=24,
      observed_time_series=observed_time_series,
      name='hour_of_day_effect')
  ghi_effect = sts.LinearRegression(
      design_matrix=tf.reshape(data.Ghi - np.mean(data.Ghi),
                               (-1, 1)), name='ghi_effect')
  ebh_effect = sts.LinearRegression(
      design_matrix=tf.reshape(data.Ebh - np.mean(data.Ebh),
                               (-1, 1)), name='ebh_effect')
  dni_effect = sts.LinearRegression(
      design_matrix=tf.reshape(data.Dni - np.mean(data.Dni),
                               (-1, 1)), name='dni_effect')
  dhi_effect = sts.LinearRegression(
      design_matrix=tf.reshape(data.Dhi - np.mean(data.Dhi),
                               (-1, 1)), name='dhi_effect')
  cloud_effect = sts.LinearRegression(
      design_matrix=tf.reshape(data.CloudOpacity - np.mean(data.CloudOpacity),
                               (-1, 1)), name='cloud_effect')
  autoregressive = sts.Autoregressive(
      order=1,
      observed_time_series=observed_time_series,
      name='autoregressive')
  model = sts.Sum([hour_of_day_effect,
                   ghi_effect,
                   ebh_effect,
                   dni_effect,
                   dhi_effect,
                   cloud_effect,
                   autoregressive],
                   observed_time_series=observed_time_series)
  return model
```

Model Fitting

Variational Inference (VI)

```
pv_model = build_model(training_data.Ppv1)

# Build the variational surrogate posteriors `qs`.
variational_posteriors = tfp.sts.build_factored_surrogate_posterior(model=pv_model)
```

```
# Allow external control of optimization to reduce test runtimes.
num_variational_steps = 200 # @param { isTemplate: true}
num_variational_steps = int(num_variational_steps)

# Build and optimize the variational loss function.
elbo_loss_curve = tfp.vi.fit_surrogate_posterior(
    target_log_prob_fn = pv_model.joint_distribution(
        observed_time_series = training_data.Ppv1).log_prob,
    surrogate_posterior = variational_posteriors,
    optimizer = tf.optimizers.Adam(learning_rate=0.1),
    num_steps = num_variational_steps,
    jit_compile = True)
plt.plot(elbo_loss_curve)
plt.show()

# Draw samples from the variational posterior.
q_samples_pv_ = variational_posteriors.sample(50)
```



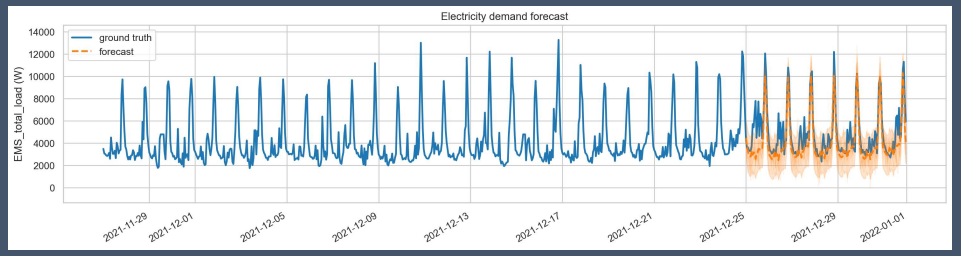
Forecasting

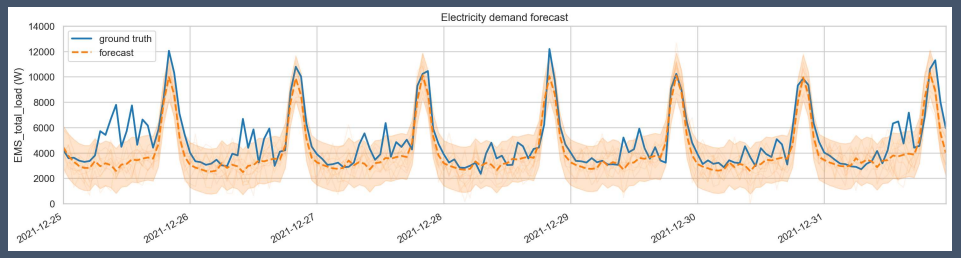
```
pv_forecast_dist = tfp.sts.forecast(
    model = pv_model,
    observed_time_series = training_data.Ppv1,
    parameter_samples = q_samples_pv_,
    num_steps_forecast = num_forecast_steps)
```

```
num_samples=10

(
    demand_forecast_mean,
    demand_forecast_scale,
    demand_forecast_samples
) = (
    demand_forecast_dist.mean().numpy()[..., 0],
    demand_forecast_dist.stddev().numpy()[..., 0],
    demand_forecast_dist.sample(num_samples).numpy()[..., 0]
    )
```

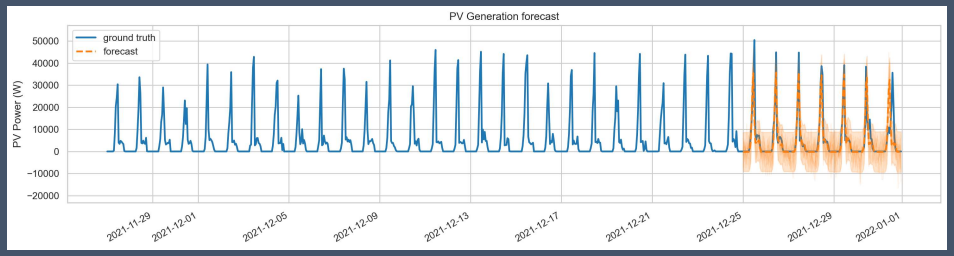
Forecasting

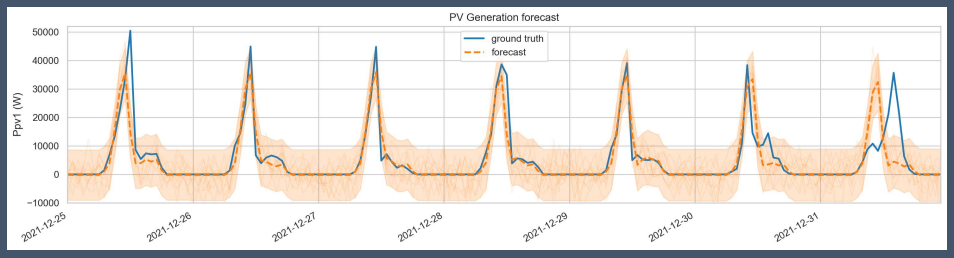
Electrical Load





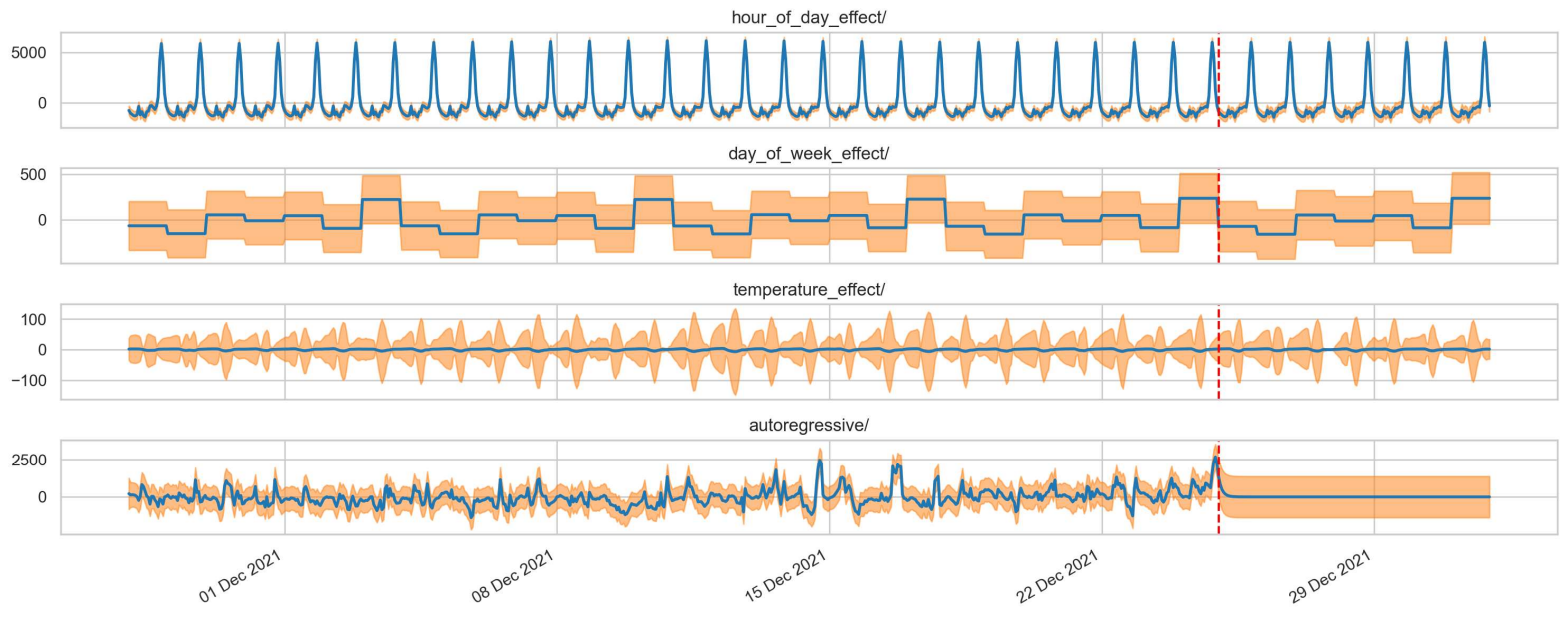
PV Generation





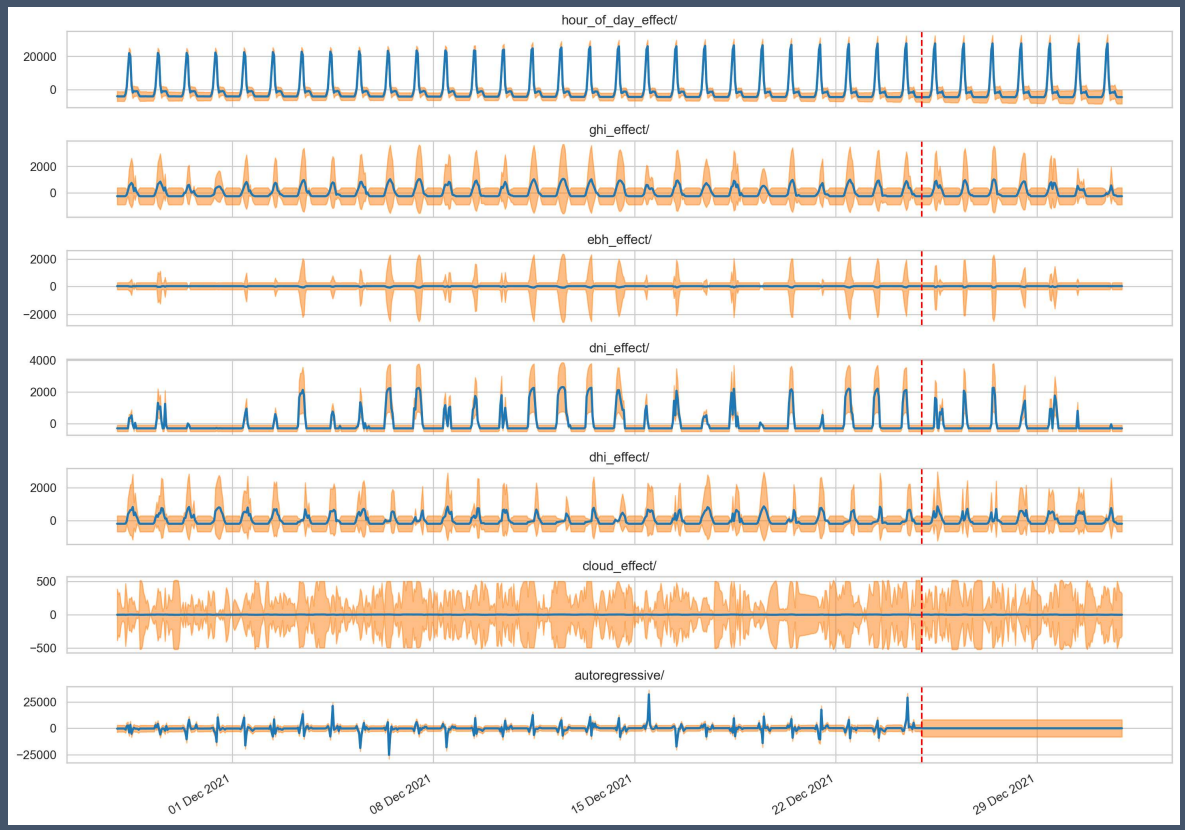
Decomposition

Electrical Load

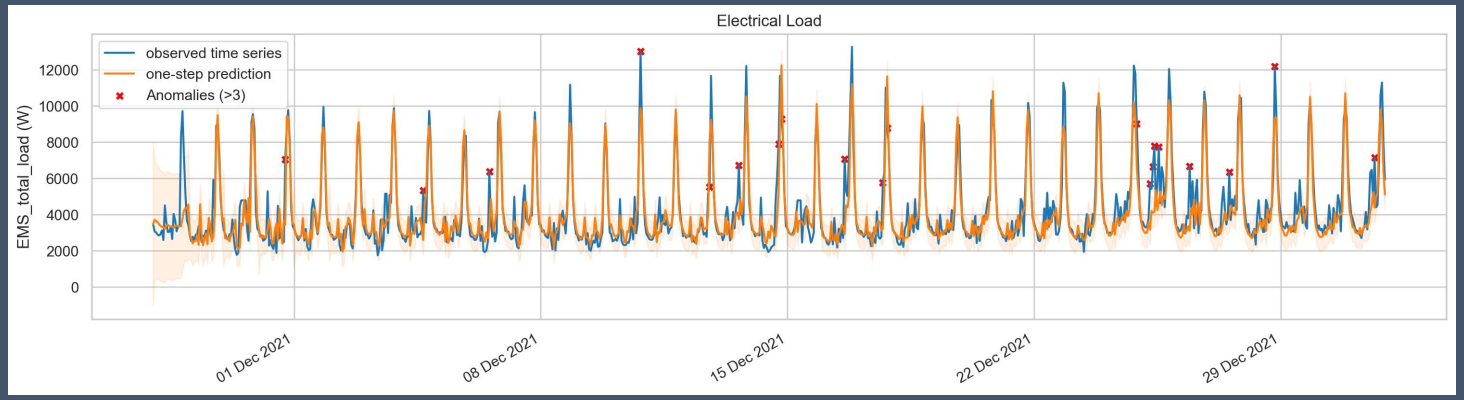


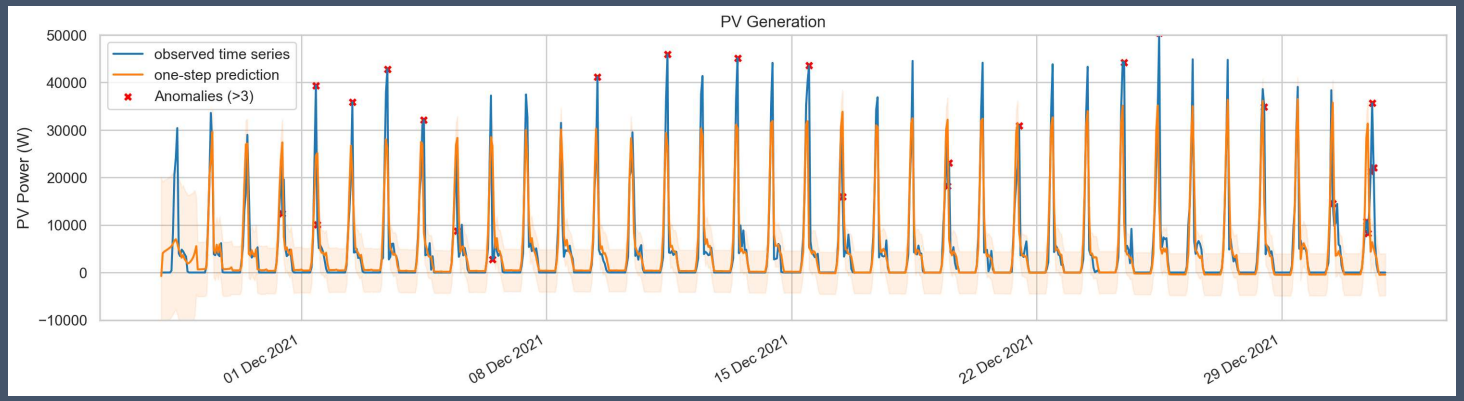
Decomposition

PV Generation



Single-step Forecasts



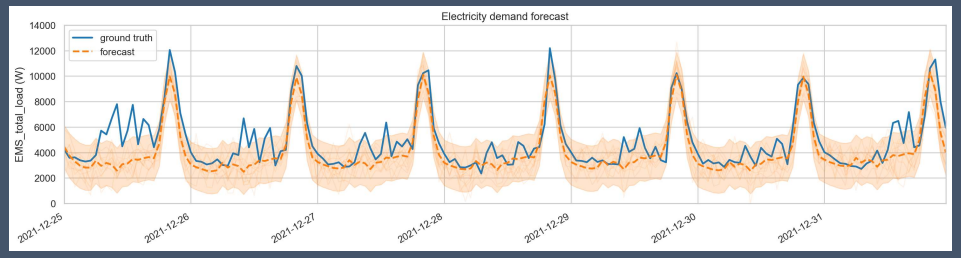


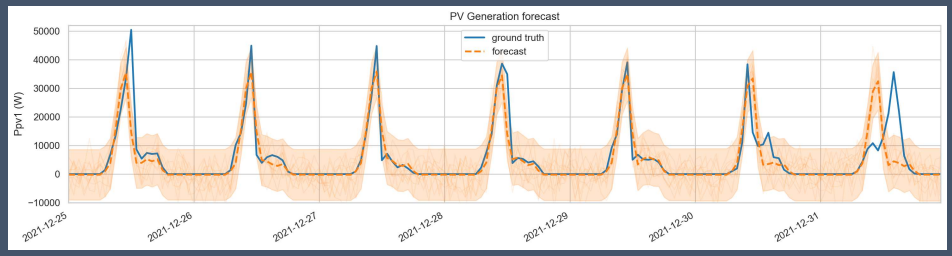
STS vs NN

Electrical Load

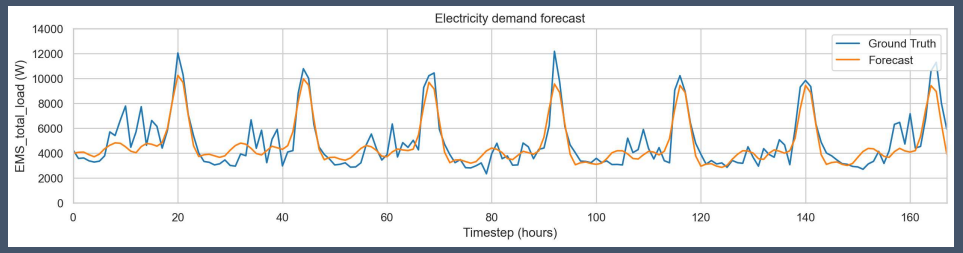
PV Generation

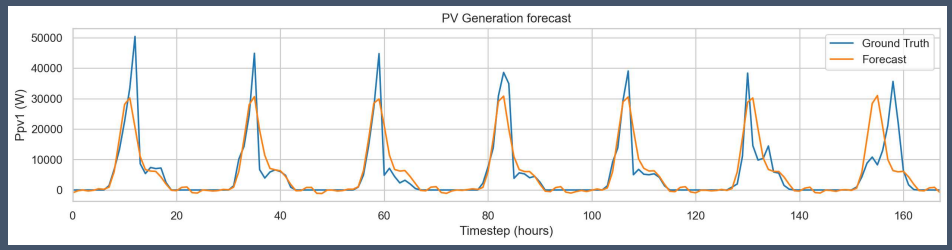
STS





NN





Summary

- **Python** and **TensorFlow** are useful tools for time series forecasting
- **Neural Networks** and **Structural Time Series** are two powerful methods of forecasting.
- Link to Jupyter Notebooks and Exercises: https://github.com/isaacflower/resilient_project_ts_forecasting