Modeling Real Data

INTRODUCTION TO LINEAR MODELING IN PYTHON

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Scikit-Learn

```
from sklearn.linear_model import LinearRegression
# Initialize a general model
model = LinearRegression(fit_intercept=True)
```

```
# Load and shape the data
x_raw, y_raw = load_data()
x_data = x_raw.reshape(len(y_raw),1)
y_data = y_raw.reshape(len(y_raw),1)
```

```
# Fit the model to the data
model_fit = model.fit(x_data, y_data)
```

Predictions and Parameters

```
# Extract the linear model parameters
intercept = model.intercept_[0]
slope = model.coef_[0,0]
```

```
# Use the model to make predictions
future_x = 2100
future_y = model.predict(future_x)
```

statsmodels

```
x, y = load_data()
df = pd.DataFrame(dict(times=x_data, distances=y_data))
```

```
fig = df.plot('times', 'distances')
```

```
model_fit = ols(formula="distances ~ times", data=df).fit()
```

Uncertainty

```
a0 = model_fit.params['Intercept']
a1 = model_fit.params['times']
```

```
e0 = model_fit.bse['Intercept']
e1 = model_fit.bse['times']
```

```
intercept = a0
slope = a1
uncertainty_in_intercept = e0
uncertainty_in_slope = e1
```

Let's practice!

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The Limits of Prediction

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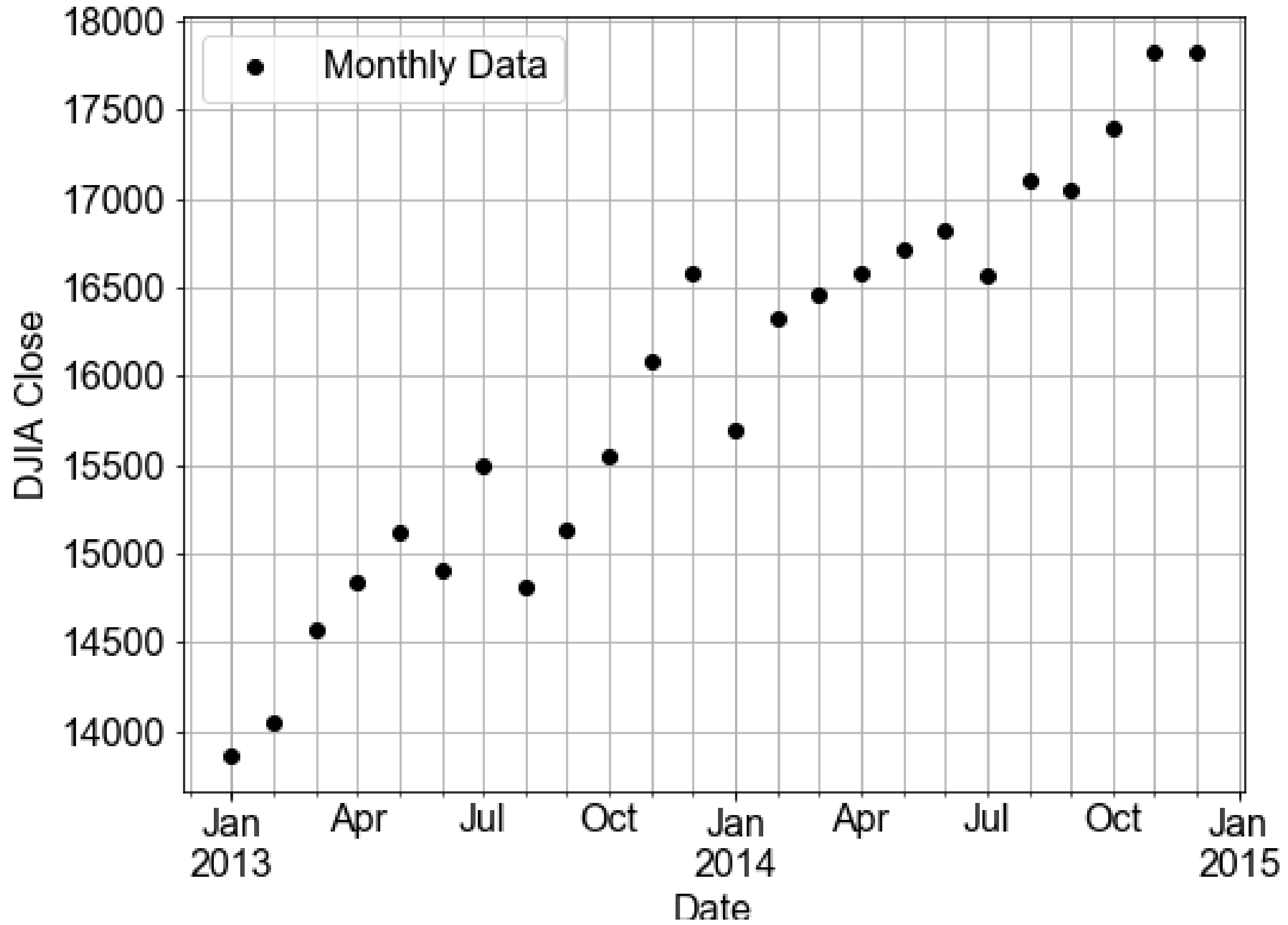
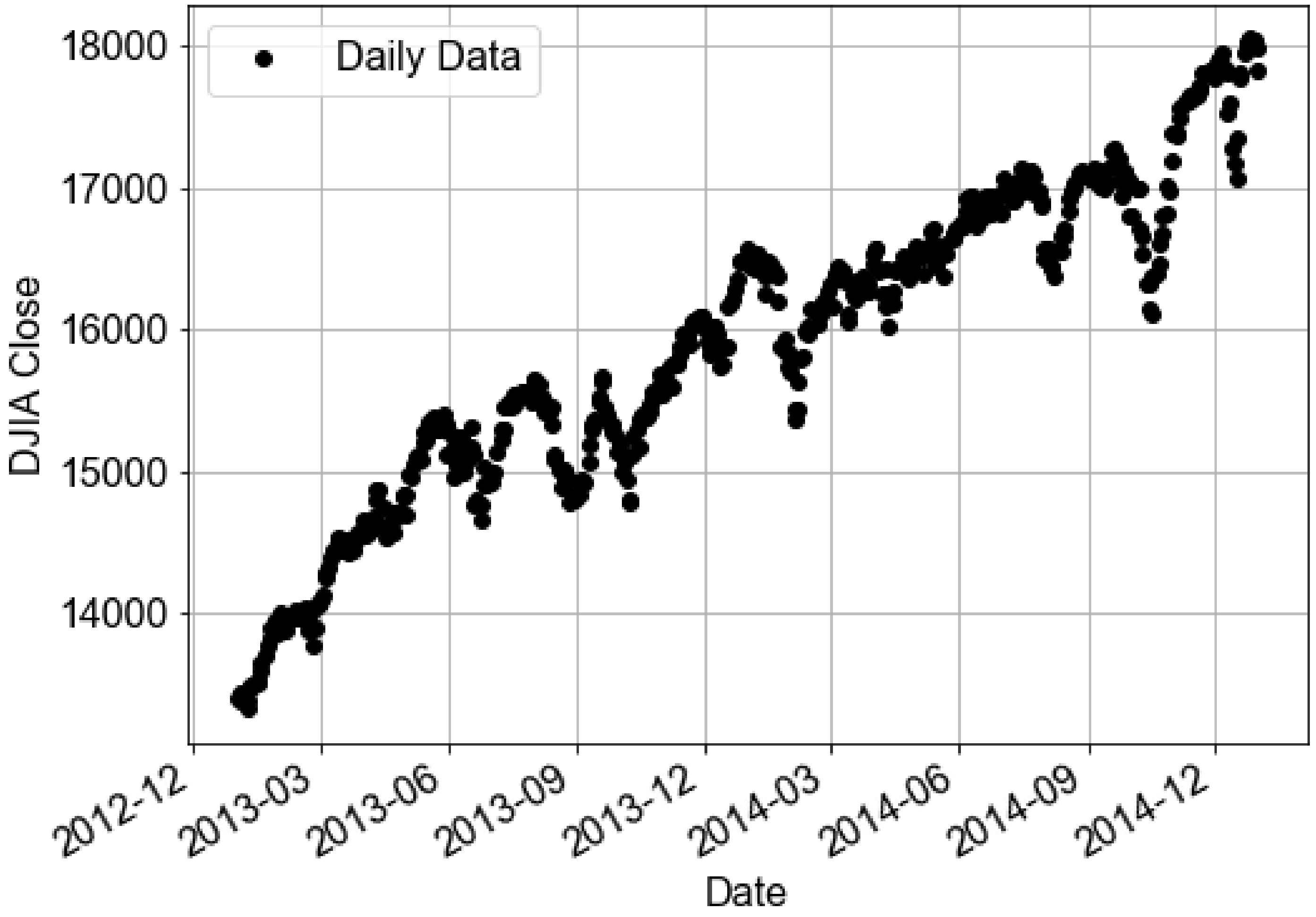
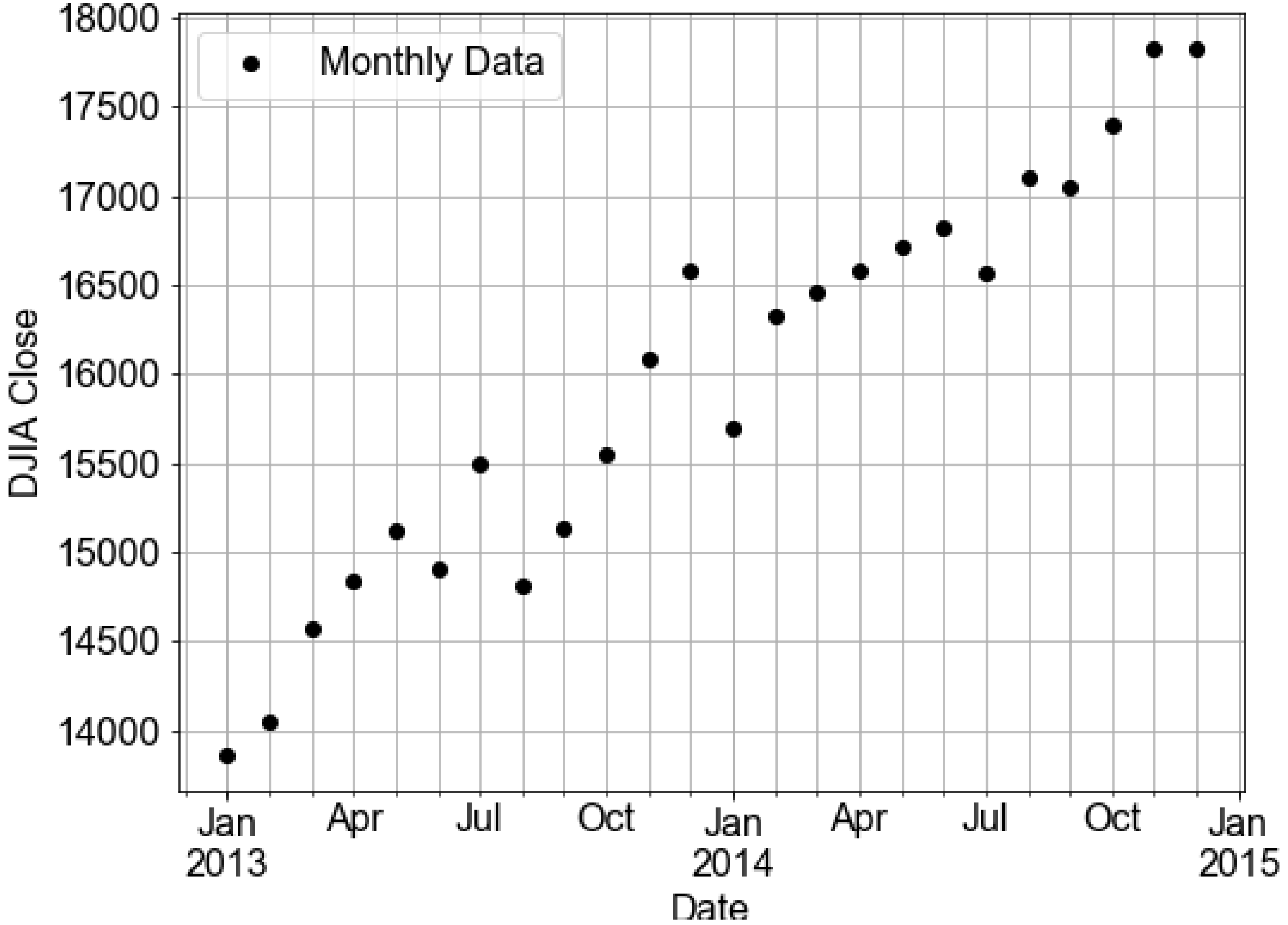
Interpolation



Interpolation



Interpolation



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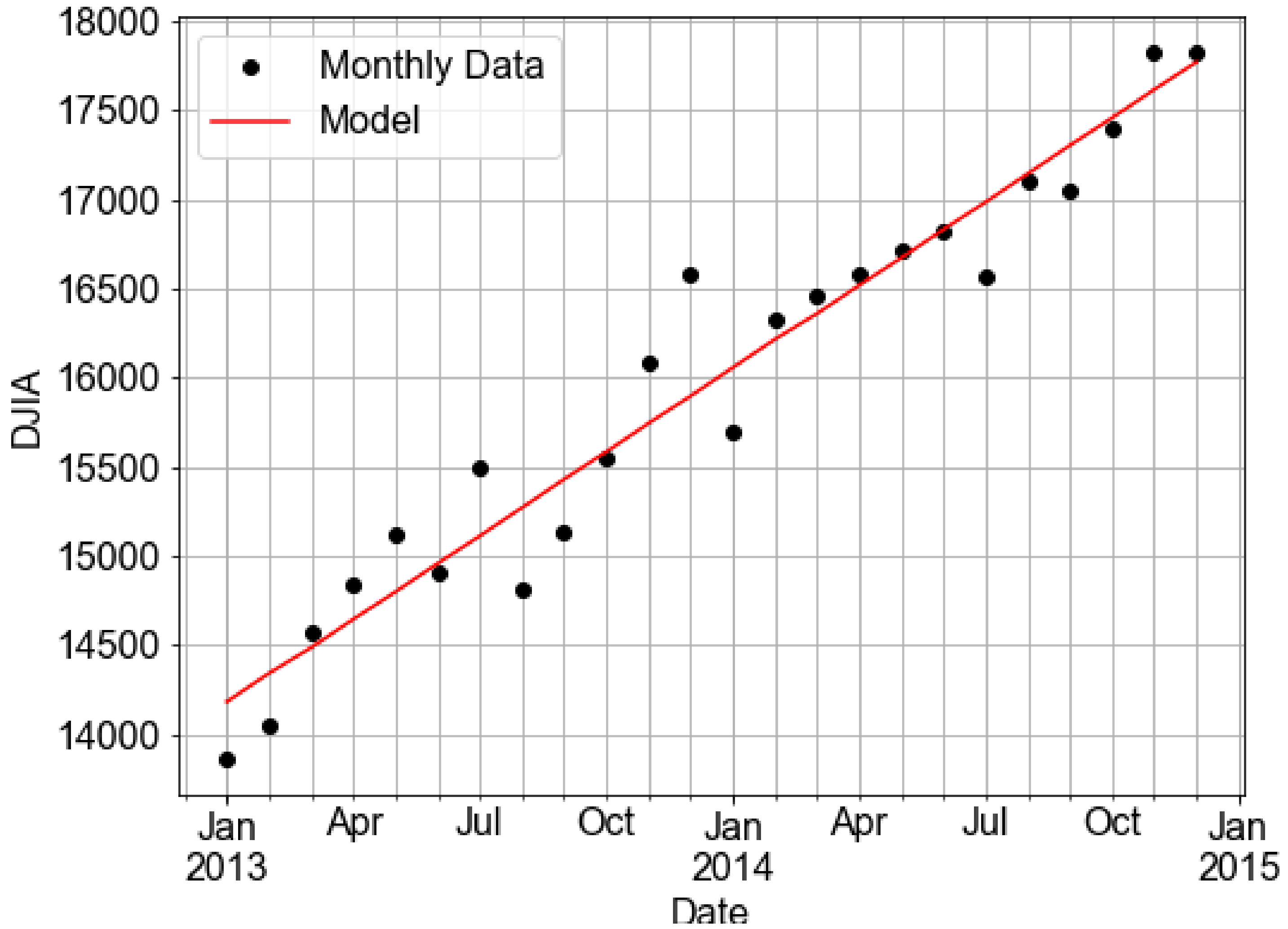
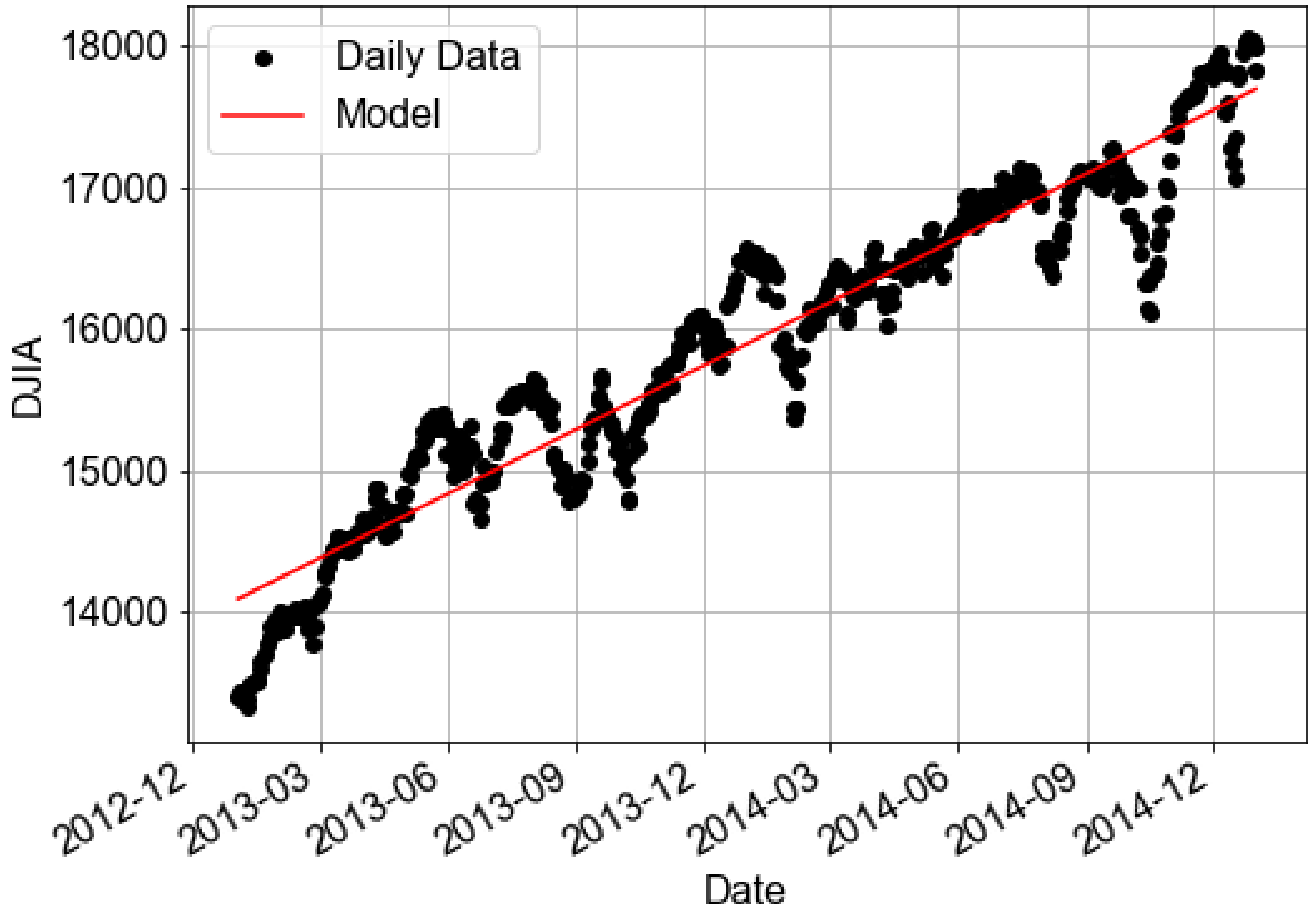


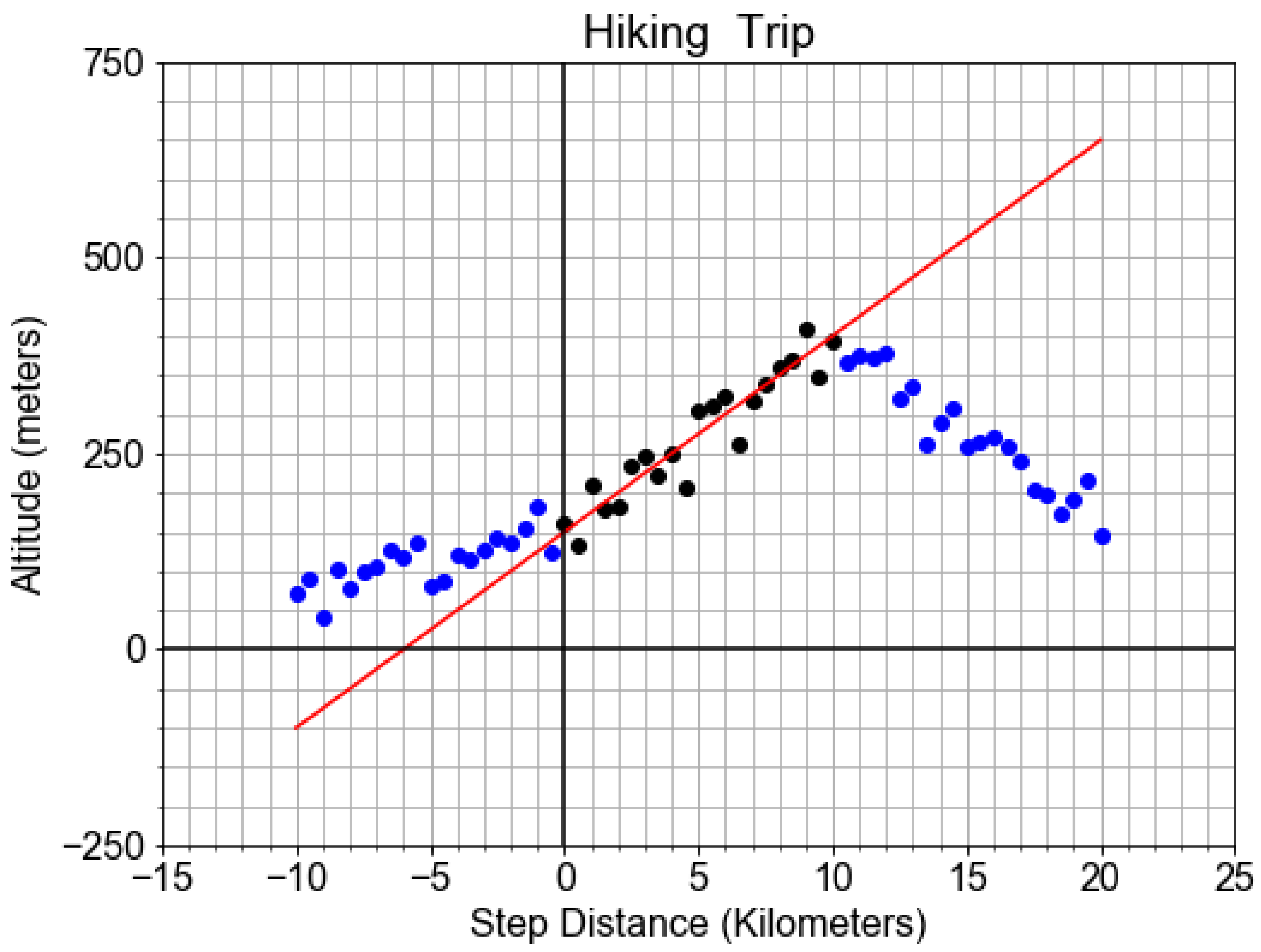
Interpolation



Domain of Validity

- zoom in: data looks linear
- model assumption: `a2*x**2 + a3*x**3` + ... = zero.
- build a linear model: `a0 + a1*x`
- zoom out: your model breaks

Extrapolating Too Far



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Goodness-of-Fit

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3 Different R's

Building Models:

- RSS

Evaluating Models:

- RMSE
- R-squared

RMSE

```
residuals = y_model - y_data
RSS = np.sum( np.square(residuals) )
```

```
mean_squared_residuals = np.sum( np.square(residuals) ) / len(residuals)
```

```
MSE = np.mean( np.square(residuals) )
```

```
RMSE = np.sqrt(np.mean( np.square(residuals)))
```

```
RMSE = np.std(residuals)
```

R-Squared in Code

Deviations:

```
deviations = np.mean(y_data) - y_data
VAR = np.sum(np.square(deviations))
```

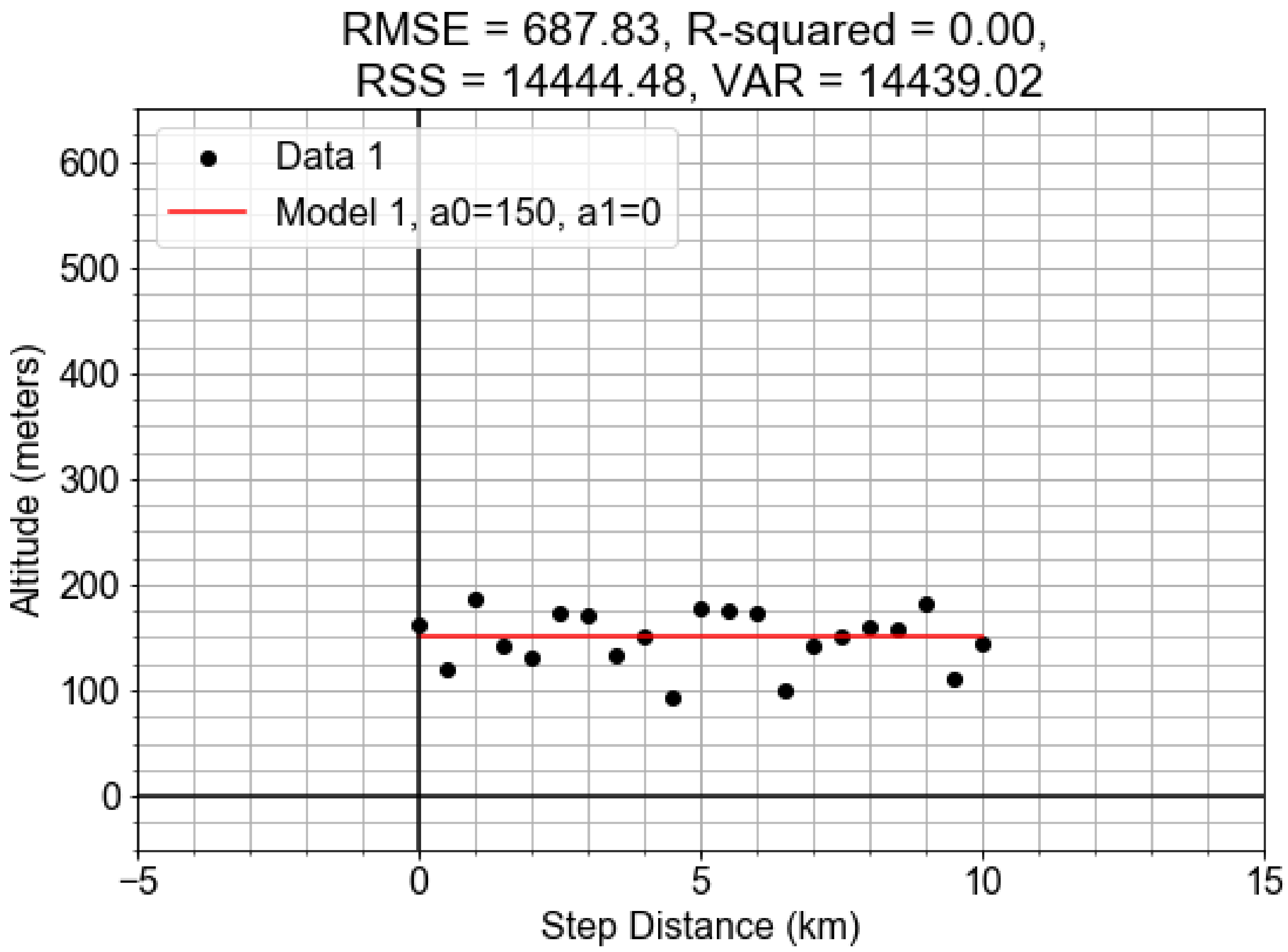
Residuals:

```
residuals = y_model - y_data
RSS = np.sum(np.square(residuals))
```

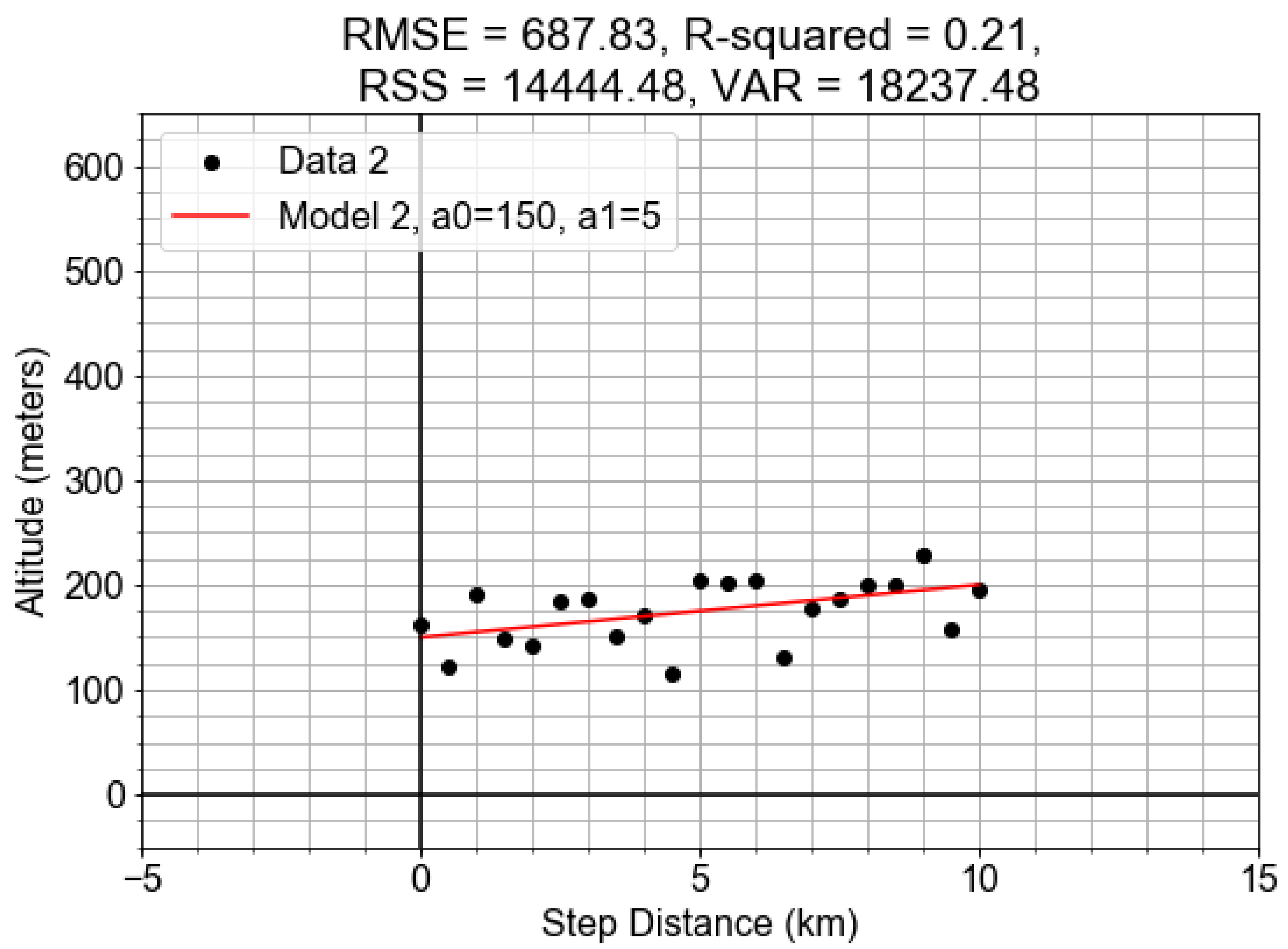
R-squared:

```
r_squared = 1 - (RSS / VAR)
r = correlation(y_data, y_model)
```

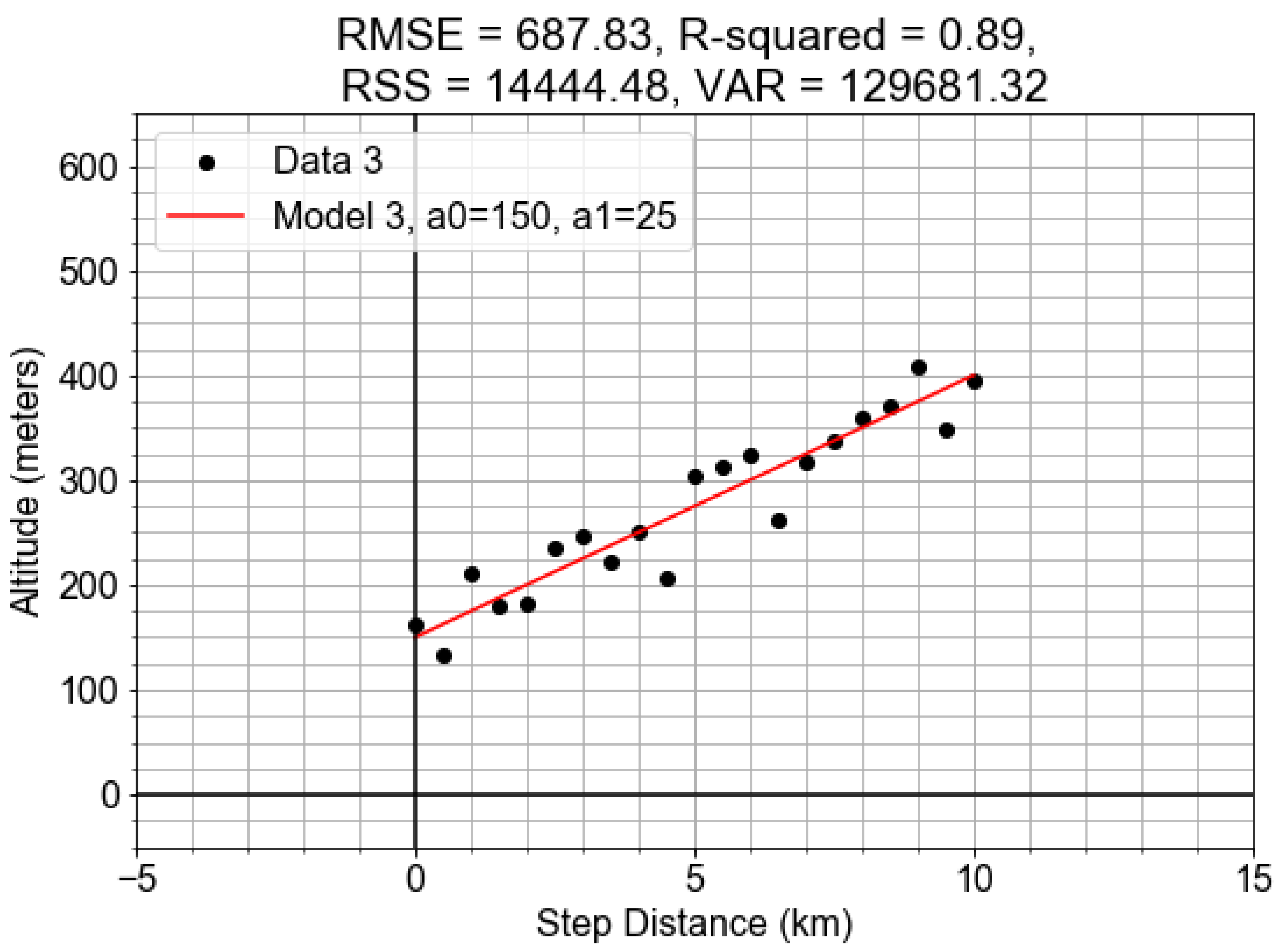
R-Squared in Data



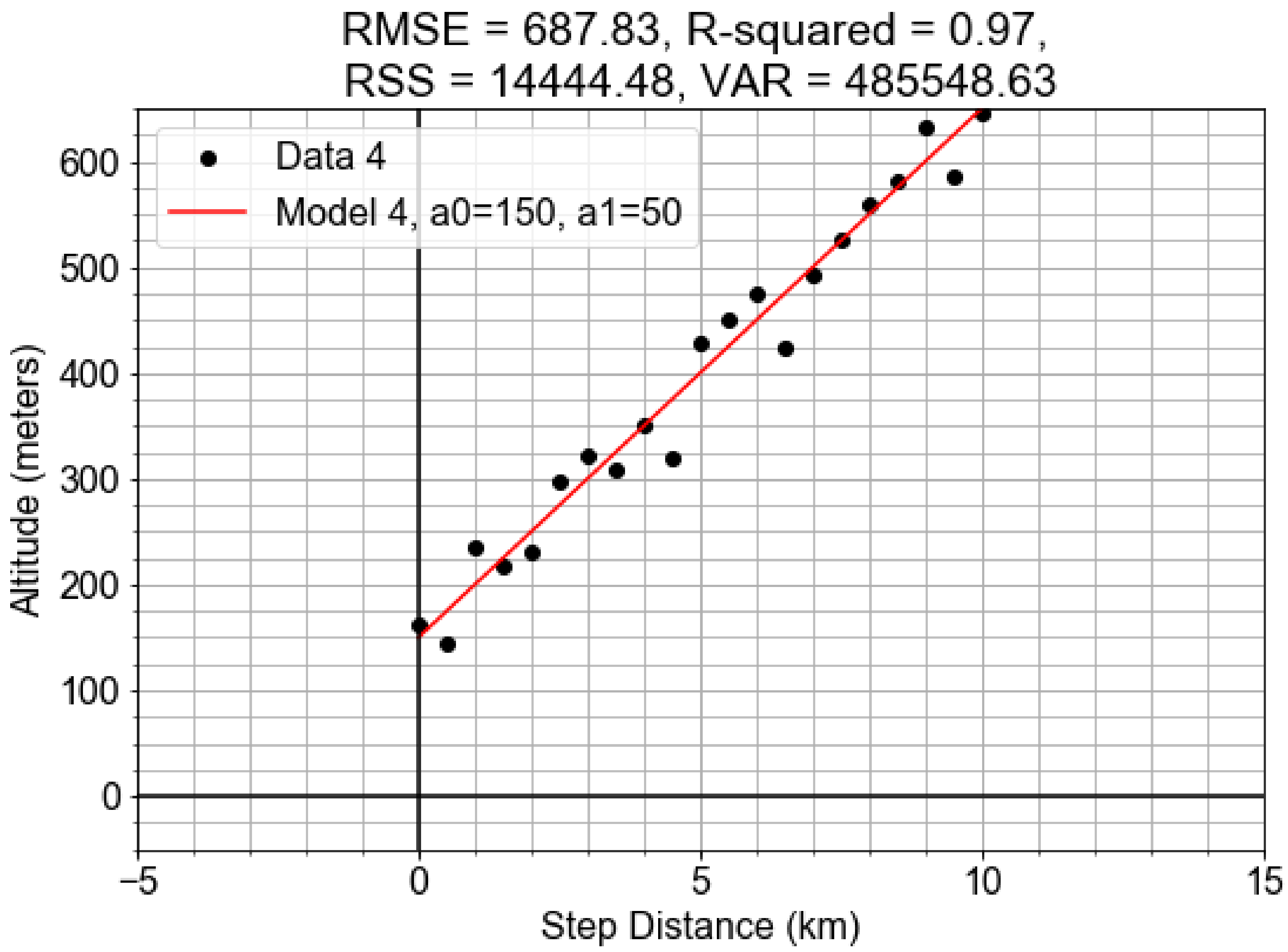
R-Squared in Data



R-Squared in Data



R-Squared in Data



RMSE vs R-Squared

- RMSE: how much variation is residual
- R-squared: what fraction of variation is linear

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Standard Error

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Uncertainty in Predictions

Model Predictions and RMSE:

- predictions compared to data gives residuals
- residuals have spread
- RMSE, measures residual spread
- RMSE, quantifies prediction goodness

Uncertainty in Parameters

Model Parameters and Standard Error:

- Parameter value as center
- Parameter standard error as spread
- Standard Error, measures parameter uncertainty

Computing Standard Errors

```
df = pd.DataFrame(dict(times=x_data, distances=y_data))
```

```
model_fit = ols(formula="distances ~ times", data=df).fit()
```

```
a1 = model_fit.params['times']
a0 = model_fit.params['Intercept']
```

```
slope = a1
intercept = a0
```

Computing Standard Errors

```
e0 = model_fit.bse['Intercept']
e1 = model_fit.bse['times']
```

```
standard_error_of_intercept = e0
standard_error_of_slope = e1
```

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