🌡️ Example 1 — Daily Temperatures Forecasting (10 Questions)

Q1. Why are lag features useful for temperature forecasting?

A. They encode temporal memory
B. They reduce noise in the data
C. They convert the series to supervised format
D. They capture autocorrelation

✔ Correct: A, C, D

Explanation:

- A: Correct — lag features give the model access to past temperatures.
- B: Incorrect — rolling features smooth noise, not lag features.
- C: Correct — lag features turn sequential data into tabular supervised form.
- D: Correct — temperature exhibits strong autocorrelation.

Q2. What does `rolling_mean_7` represent?

A. Trend over past 7 days
B. Noise reduction via smoothing
C. Seasonality detection
D. Volatility measurement

✔ Correct: A, B

Explanation:

- A: Correct — rolling mean smooths and reveals local trend.
- B: Correct — smoothing reduces short-term spikes.
- C: Incorrect — seasonality requires broader windows or calendar features.

- D: Incorrect — rolling *std* captures volatility.

Q3. Why use a naive baseline (`lag_1`) in temperature forecasting?

A. It is simple and surprisingly strong
B. Temperatures usually don't change drastically day-to-day
C. It guarantees the best accuracy
D. It helps evaluate if ML adds value

✔ Correct: A, B, D

Explanation:

- A: Correct — `temp[t] ≈ temp[t-1]` often works well.
- B: Correct — temperatures are highly autocorrelated.
- C: Incorrect — no guarantee.
- D: Correct — baseline comparison is essential.

Q4. Why avoid shuffling the dataset?

A. It destroys the temporal order
B. It causes data leakage
C. It improves randomness
D. Time-series models require chronological structure

✔ Correct: A, B, D

Q5. Why does Random Forest work well with temperature data?

A. Handles non-linear relationships
B. Leverages lag/rolling features effectively

C. Automatically detects seasonality
D. Robust to noise

✔ Correct: A, B, D

Q6. What does rolling standard deviation tell us?

A. Local volatility
B. Trend strength
C. Noise level
D. Seasonality amplitude

✔ Correct: A, C

Q7. What is the purpose of dropping NaNs after feature creation?

A. Remove incomplete rows
B. Prevent training errors
C. Improve model accuracy
D. Maintain chronological order

✔ Correct: A, B

Q8. In a daily series, why choose small lag values like 1,2,3?

A. Daily temperatures correlate strongly with recent days
B. Large lags cause overfitting
C. Longer historical memory is unnecessary
D. Trend can be captured via rolling windows instead

✔ Correct: A, D

Q9. What is one-step-ahead forecasting?

A. Predicting next time step only
B. Requires the most recent features
C. Same as multi-step forecasting
D. Uses the model recursively

✔ Correct: A, B

Q10. What does a lower MAE than the baseline indicate?

A. ML model adds predictive value
B. Feature engineering worked
C. Overfitting occurred
D. Forecast quality improved

✔ Correct: A, B, D

✈️ Example 2 — Airline Passenger Forecasting (10 Questions)

Q1. Why is a log transform used for airline passengers?

A. Stabilize variance
B. Convert multiplicative patterns into additive
C. Remove trend completely
D. Help models learn smoother relationships

✔ Correct: A, B, D

Q2. Why include `lag_12`?

A. Captures yearly seasonality
B. Airline demand cycles repeat yearly
C. Removes trend
D. Adds long-term memory

✔ Correct: A, B, D

Q3. Why add month-of-year one-hot encoding?

A. Encodes seasonality explicitly
B. Makes the model aware of month differences
C. Removes noise
D. Helps predict peaks in summer travel

✔ Correct: A, B, D

Q4. Why use 12-month rolling mean?

A. Capture yearly trend
B. Smooth seasonal fluctuations
C. Remove all noise completely
D. Provide long-term trend signal

✔ Correct: A, D

Q5. Why compare log-MAE instead of raw MAE?

A. Log transform compresses scale
B. Errors represent relative differences
C. Raw values exaggerate late-year errors
D. It removes seasonality

✔ Correct: A, B, C

Q6. Why Random Forest cannot detect seasonality without features?

A. Trees do not understand sequences
B. Raw time-series provides no positional context
C. Random Forest only sees tabular rows
D. It relies on engineered seasonal inputs

✔ Correct: A, B, C, D

Q7. Why naive forecast (lag_1) is strong here?

A. Monthly values change slowly
B. Airline passengers show short-term persistence
C. Seasonality only affects long-term patterns
D. Last month's value is often close to next month's

✔ Correct: A, B, D

Q8. Why is trend important in the airline dataset?

A. Air travel grew significantly over the years
B. Trend influences yearly peaks
C. Lag features alone cannot capture long-term growth
D. Rolling features help reveal underlying direction

✔ Correct: A, C, D

Q9. Why must calendar features be one-hot encoded?

A. ML models cannot interpret raw month numbers
B. Prevent the model from assuming ordinal relationship
C. Encode seasonality cleanly
D. Improve model interpretability

✔ Correct: A, B, C

Q10. What makes airline forecasting more challenging?

A. Seasonal peaks and troughs
B. Exponential growth trend
C. Non-stationary behavior
D. Noise from travel patterns

✔ Correct: A, B, C, D

🥛 Example 3 — Monthly Milk Production Forecasting (10 Questions)

Q1. Why is `lag_12` essential for milk production forecasting?

A. Strong annual seasonality
B. Milk output cycles yearly
C. Captures same month last year
D. Removes short-term noise

✔ Correct: A, B, C

Q2. Why include rolling mean (12-month)?

A. Track long-term trend
B. Smooth month-to-month fluctuations
C. Capture cycle amplitude
D. Encode average yearly production

✔ Correct: A, B, D

Q3. What does rolling standard deviation capture?

A. Stability of production
B. Variability across the year
C. Seasonal peak size
D. Noise in agricultural output

✔ Correct: A, D

Q4. Why do milk datasets have smoother cycles?

A. Biological patterns in cows
B. Consistent seasonal rhythms
C. Low external volatility
D. Stable agricultural processes

✔ Correct: A, B, D

Q5. Why is the naive baseline fairly strong for milk?

A. Month-to-month changes are moderate
B. Short-term autocorrelation is high
C. Cycles are smooth
D. Lag_1 holds meaningful information

✔ Correct: A, B, C, D

Q6. Why add month-of-year one-hot encoding here?

A. Monthly production repeats annually
B. Seasonal cycles dominate the series
C. Helps model learn seasonal peaks
D. Reduce need for large lag values

✔ Correct: A, B, C

Q7. Why drop the first 12 rows after feature engineering?

A. Lag_12 is undefined initially
B. Rolling windows require 12 observations
C. Missing values break training
D. It improves stationarity

✔ Correct: A, B, C

Q8. Why is Random Forest effective on milk series?

A. Handles non-linear seasonal cycles
B. Works well with lag + month features
C. Robust to small dataset size
D. Captures smooth patterns easily

✔ Correct: A, B, C, D

Q9. Why avoid differencing in this example?

A. Series is already smooth
B. Trend and seasonality are easier to encode via features
C. Differencing loses interpretability
D. ML models handle non-stationary inputs with engineered features

✔ Correct: A, B, C, D

Q10. What makes milk production forecasts easier than airline passengers?

A. No exponential growth
B. Seasonality is smoother
C. Less volatility and noise
D. Series is quasi-stationary

✔ Correct: A, B, C