Outline

The problem with NaN

Real datasets have holes. A single NaN breaks math operations downstream.

Running example: Yerevan apartment rent. Some rows have unknown balcony, others have unknown year_built.

```
>>> df.head()
   area  rooms  district     year_built  balcony  rent
0  45.0     2    Kentron        1985        Yes     280
1  62.0     3    Arabkir          NaN        No     340
2   NaN     2    Komitas        1992        NaN     310
3  38.0     1    Kentron        1978        No      245

>>> (df["area"] * 1000).mean()
nan                          # one NaN poisons the whole column
```

Before any model: detect, decide, document.

Types of missingness

Why data is missing matters more than how much. Plain-English first, statistics names in parentheses:

- **Innocent missing (MCAR).** The reason a value is missing has nothing to do with any other variable. Example: random data-entry hiccup. *Safe to drop or impute.*
- **Structured missing (MAR).** Missingness depends on *other observed* variables. Example: older buildings less likely to have `year_built` recorded - missingness depends on the (observable) age. *A model can recover it from the other columns.*
- **Biased missing (MNAR).** Missingness depends on the *value itself*. Example: tenants don't report rent when it's unusually high - the value affects whether it's reported. *Dangerous - imputation will be biased; need domain reasoning.*

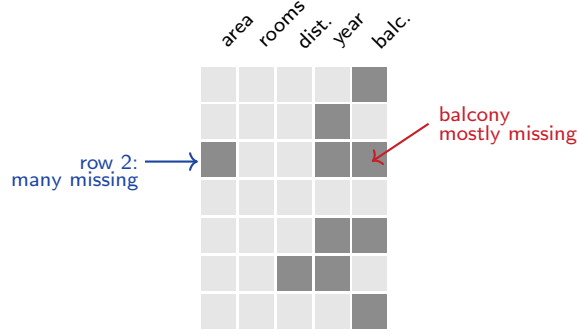
You can't fully distinguish these from data alone. You can usually rule things out by talking to whoever collected the data.

Detect: visualize the pattern

```
df.isna().sum()                    # per column
df.isna().mean() * 100             # percent
df.isna().any(axis=1).mean()       # row-wise fraction
import missingno as msno
msno.matrix(df)                    # heatmap
```

Look for two patterns:

- A **column** mostly missing ⇒ consider dropping it.
- A **row** with many missing fields ⇒ MAR pattern likely.



Strategy 1 & 2: drop vs. simple impute

Drop - cheap, sometimes wrong:

```
df.dropna()                  # any
    NaN
df.dropna(thresh=4)          # keep
    rows w/ >= 4 non-NaN
df.dropna(axis=1)            # drop
    NaN columns
```

- Use when missing rate is small ($< 5\%$) AND MCAR-ish.
- Risk: throwing away signal. If `balcony` is missing for 30% of rows, dropping them loses a third of the data.

Simple impute - fast baseline:

```
from sklearn.impute import
    SimpleImputer

num = SimpleImputer(strategy="
    median")
cat = SimpleImputer(strategy="
    most_frequent")
df["area"] = num.fit_transform(df
    [["area"]])
```

- Numeric: median (robust to outliers), mean (only if symmetric).
- Categorical: mode.
- Constants: `fill_value=0` or `"Unknown"`.

Predict-first: what does mean imputation hide?

You have area data for 100 apartments. 20 values are missing. You fill the 20 holes with the mean of the other 80.

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- What happens to the *variance* of the column?
- What happens to its *correlation* with rent?
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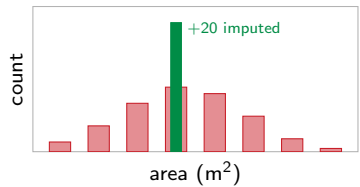
- **Variance shrinks** - the 20 imputed values are identical, so they contribute 0 to spread.
- **Correlation attenuates** - 20 rows say "I am the mean" regardless of rent.
- **Confidence is overstated** - the model treats imputed values as real measurements.

Mean imputation is a fine baseline, but it lies about uncertainty.



Green spike at the mean = lost variance.

Smarter imputation + the indicator trick

Model-based imputation. Predict each missing value from the other features.

```
from sklearn.impute import KNNImputer, IterativeImputer
KNNImputer(n_neighbors=5).fit_transform(X)
IterativeImputer(random_state=509).fit_transform(X)    # ~MICE
```

- KNN: find the 5 most similar rows, average their value.
- Iterative (MICE-style): regress each column on the others, loop until stable.
- Cost: slower, can leak if not fit on train only.

Missingness as a feature. Add a binary indicator column:

```
df["balcony_missing"] = df["balcony"].isna().astype(int)
df["balcony"] = df["balcony"].fillna("Unknown")
```

Why: *the fact that something is missing* can itself be predictive. A landlord who didn't report `year_built` may be hiding a very old building.

Two more cleanups: duplicates and outliers

Duplicates.

```
df.duplicated().sum()              # count
df.drop_duplicates()               # exact
df.drop_duplicates(                # subset
    subset=["area","rooms","district"])
```

- Exact duplicates: usually safe to drop.
- *Near*-duplicates (same apartment listed twice with tiny price diff): need a domain rule.
- Sometimes duplicates are real (two units of one model car) - check before dropping.

Outliers.

```
# IQR rule (Tukey)
q1, q3 = df["rent"].quantile([.25, .75])
iqr = q3 - q1
mask = df["rent"].between(q1 - 1.5*iqr,
                          q3 + 1.5*iqr)
# z-score rule
from scipy.stats import zscore
mask = abs(zscore(df["rent"])) < 3
# model-based: IsolationForest (sklearn)
```

- Don't drop blindly. Investigate first.
- Outliers are often data-entry errors OR the most interesting rows.

Why encode at all?

Most ML models (linear regression, k-NN, gradient boosting trees, neural networks) operate on **numbers**. They can't multiply, take dot products with, or compute distances on the string `"Kentron"`.

Encoding turns categorical strings (or category codes) into numerical features that preserve the right structure.

Pick the encoding by two questions:

1. **Are the categories ordered?** (e.g., *small* $<$ *medium* $<$ *large*.)
2. **How many unique values?** (Few $\rightarrow$ one-hot is fine. Many $\rightarrow$ one-hot explodes.)

One-hot encoding: the default for unordered

Each category becomes its own 0/1 column.

Before:

district
Kentron
Arabkir
Komitas
Kentron

After one-hot:

d=Kentron	d=Arabkir	d=Komitas
1	0	0
0	1	0
0	0	1
1	0	0

```
pd.get_dummies(df, columns=["district"], drop_first=False)
from sklearn.preprocessing import OneHotEncoder
OneHotEncoder(handle_unknown="ignore", sparse_output=False)
```

Production essential: `handle_unknown="ignore"`. Otherwise an unseen test-set district crashes the model. `drop="first"` also matters - next slide.

The dummy trap (link back to L01b)

Including *all* one-hot columns AND an intercept makes the design matrix singular:

$$\underbrace{1}_{\text{intercept}} = \underbrace{\mathbb{1}[d{=}\text{Kentron}] + \mathbb{1}[d{=}\text{Arabkir}] + \mathbb{1}[d{=}\text{Komitas}]}_{\text{sum of all dummies}}$$

The all-ones column equals the sum of the dummies. Columns are linearly dependent $\Rightarrow \mathbf{X}^\top\mathbf{X}$ not invertible $\Rightarrow$ OLS fails (L01b Section 4).

Two fixes:

- `pd.get_dummies(..., drop_first=True)` - drops one category, which becomes the reference baseline absorbed into θ_0.
- `OneHotEncoder(drop="first")` (sklearn).

Exceptions where you keep ALL dummies:

- Ridge / Lasso (regularization makes the system invertible anyway).
- Trees (no intercept, no matrix inversion).
- When you want all coefficients interpretable on the same footing (no reference category).

Label / ordinal encoding: ONLY for ordered

Maps each category to an integer. **Imposes an order.**

```
from sklearn.preprocessing import OrdinalEncoder
# CORRECT use: t-shirt sizes
OrdinalEncoder(categories=[["S","M","L","XL"]]).fit_transform(...)
# WRONG use: city names
OrdinalEncoder().fit_transform(df[["district"]])  # treats Kentron=0
    < Arabkir=1 < Komitas=2
```

The common mistake: feeding label-encoded city names to a linear regression. The model sees Komitas = 2× Arabkir, which is nonsense.

Rule: use ordinal encoding only when you can write down the order on paper and defend it.

High-cardinality: target and frequency encoding

Some categoricals have hundreds or thousands of levels (zip codes, product IDs). One-hot explodes; ordinal lies. Two production tricks:

Target encoding. Replace each category by the mean target value among rows of that category.

```
# example: district -> mean rent in that district (computed on TRAIN
    only!)
mean_rent = df_train.groupby("district")["rent"].mean()
df["district_te"] = df["district"].map(mean_rent)
```

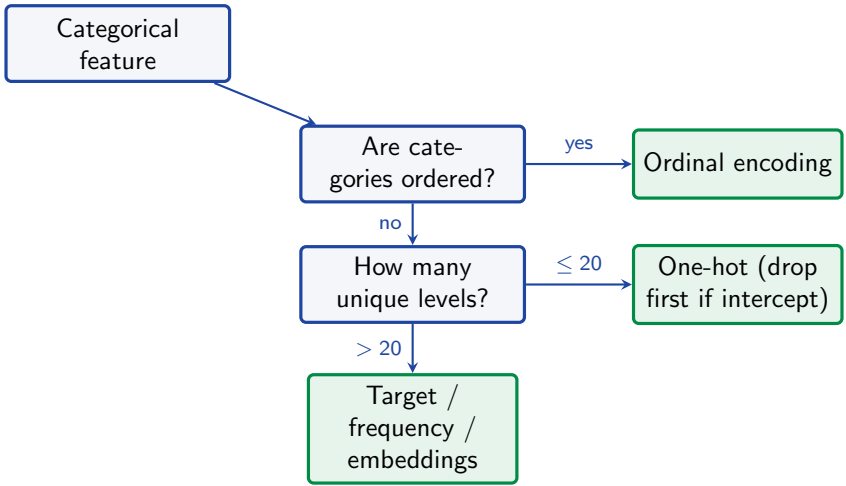
Why this is leakage if computed on full data: the mean depends on `rent`, which is what you're predicting. If you compute the mean using test rows, you've used the answer as an input.

Frequency / count encoding. Replace each category by how often it appears.

```
freq = df_train["district"].value_counts(normalize=True)
df["district_freq"] = df["district"].map(freq)
```

Both must be *fit on the training fold only*. Use `category_encoders` library + CV-aware variants in practice.

Encoding decision flowchart



Embeddings (a learned dense vector per category) are the modern high-cardinality default for neural networks - covered in the NN chapter.

Datetime preprocessing

Raw dates aren't directly usable. Extract components, and use *cyclic* encoding for periodic features.

```
df["dt"] = pd.to_datetime(df["listed_at"])
df["year"]    = df["dt"].dt.year
df["month"]   = df["dt"].dt.month
df["weekday"] = df["dt"].dt.dayofweek          # 0=Mon
df["hour"]    = df["dt"].dt.hour
```

Cyclic features need sin/cos encoding. `hour`=23 and `hour`=0 are 1 hour apart, not 23. Label encoding lies; one-hot wastes columns. Trick:

```
import numpy as np
df["hour_sin"] = np.sin(2 * np.pi * df["hour"] / 24)
df["hour_cos"] = np.cos(2 * np.pi * df["hour"] / 24)
```

Also useful: time since a reference event (`days_since_listed`), holiday indicators, weekend flag.

Predict-first: why scale?

You have three features:

- `area` in m^2, ranging 20-200
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Predict before reading on:

- In k-NN with Euclidean distance, which feature dominates the neighbor calculation?
- In gradient descent on linear regression, does the step size that works for θ_{area} also work for θ_{year}?
- Do decision trees care about feature scale at all?

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Answers: kNN distance is dominated by `year_built` (largest range). GD oscillates: one good learning rate per feature is impossible. Trees: **no** - they only use threshold comparisons.

Three scalers: formulas + when to use

StandardScaler (z-score):

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

Output: mean 0, std 1.

Best for *roughly Gaussian* features. Default choice for linear models.

MinMaxScaler:

$$x' = \frac{x - \min}{\max - \min}$$

Output: range $[0, 1]$.

Best for *bounded inputs* (image pixels, percentages, anything with natural floor/ceiling).

RobustScaler:

$$x' = \frac{x - \text{med}}{\text{IQR}}$$

Output: median 0, IQR 1.

Best when *outliers* would distort mean/std. Uses median + IQR instead.

- All three are linear ($x' = a\,x + b$). They don't change the *shape* of the distribution.
- For a skewed feature: apply log / power transform *first*, then scale.

Three scalers: code comparison

Same interface for all three - drop-in replaceable:

```
from sklearn.preprocessing import StandardScaler, MinMaxScaler,
    RobustScaler

# 1. Standardize (z-score)
sc = StandardScaler().fit(X_train)
X_train_z = sc.transform(X_train)
X_test_z  = sc.transform(X_test)          # NEVER refit on test

# 2. Min-max to [0, 1]
mm = MinMaxScaler().fit(X_train)
X_train_mm = mm.transform(X_train)

# 3. Robust (median / IQR)
rs = RobustScaler().fit(X_train)
X_train_rs = rs.transform(X_train)
```

The `fit` call learns μ, σ (or min/max, or median/IQR) from *training data only*. The `transform` call applies the same statistics to both train and test. Pipelines (later) automate this.

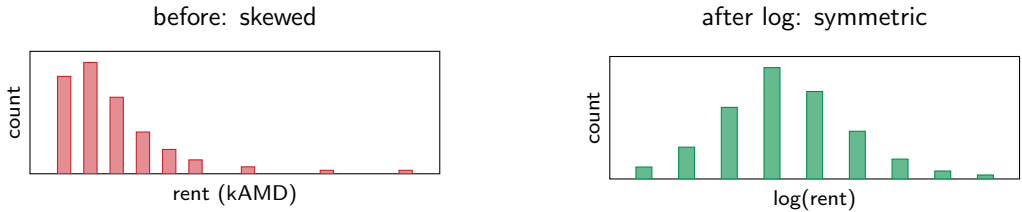
When does scaling matter?

Model family	**Scale?**	**Why**
Linear regression with GD (L02)	yes	step size needs it
Linear regression with normal eq. (L01b)	weakly	numerical conditioning
Ridge / Lasso	yes	penalty depends on coeff. magnitudes
k-NN, k-means, SVM-RBF	yes	distances dominated by big-range features
Logistic regression with GD	yes	same as linear+GD
PCA	yes	variance dominated by big-range features
Decision trees, random forests, GBMs	**no**	only use thresholds
Gaussian Naive Bayes	no	per-feature mean/var anyway

Trees only look at thresholds (`if area > 60 ...`) - rescaling doesn't change which split is best. Distance-based and gradient-based methods care a lot.

Log and power transforms for skew

`rent` is right-skewed: most apartments 200-400 kAMD, a long tail of luxury at 1500+. Models with symmetric-noise assumptions both *underfit the tail* AND *overpredict near the mean*. A monotonic transform compresses the tail and restores symmetry.




```
df["log_rent"] = np.log1p(df["rent"])                # log(1 + x), handles 0
from sklearn.preprocessing import PowerTransformer
PowerTransformer(method="yeo-johnson").fit(Xtr)      # any real input
PowerTransformer(method="box-cox").fit(Xtr)          # requires x > 0
```

After training in log-space, invert with `np.expm1` to report MAE in real units.

The leakage rule (the single most important slide)

Every preprocessor has a *state* learned from data: a mean, a list of categories, a min/max. The rule:

Fit on train. Transform on train and test.
Never fit on test. Never fit on train+test combined.

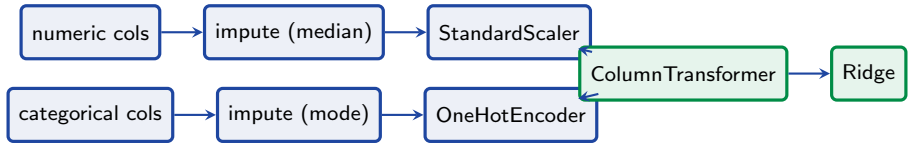
Examples of how leakage hides:

- Scaling on full data before train/test split $\Rightarrow$ test mean leaks into train.
- Mean-imputing on full data $\Rightarrow$ same.
- Target encoding on full data $\Rightarrow$ test target leaks into a feature.
- One-hot on full data $\Rightarrow$ usually OK, but unseen test categories will crash unless `handle_unknown="ignore"`.

Effect: inflated CV scores during dev, ugly surprises in production.

sklearn Pipeline + ColumnTransformer (the right way)

Wrap the chain so leakage is structurally impossible. Conceptually:




```
numeric = Pipeline([("imp", SimpleImputer(strategy="median")),
                    ("sc",  StandardScaler())])
categorical = Pipeline([("imp", SimpleImputer(strategy="most_frequent")),
                        ("ohe", OneHotEncoder(handle_unknown="ignore", drop=
                            "first"))])
pre = ColumnTransformer([("num", numeric,      ["area", "rooms", "year_built"
    ]),
                         ("cat", categorical, ["district", "balcony"])])
model = Pipeline([("pre", pre), ("ridge", Ridge(alpha=1.0))])
model.fit(X_train, y_train)          # ONE call -- no leakage possible
```

Recap

- **Missing data:** detect the pattern, prefer median/mode for a baseline, use KNN / iterative when you need accuracy, add an indicator column when missingness itself is informative. Drop duplicates after a quick sanity check. Treat outliers as signals to investigate, not noise to delete.
- **Categorical encoding:** one-hot for low cardinality (drop one column if you have an intercept - the dummy trap from L01b). Ordinal only for genuinely ordered categories. Target / frequency / embeddings for high cardinality. Cyclic sin/cos for periodic features like hour-of-day.
- **Scaling:** StandardScaler for Gaussian-ish, MinMax for bounded, Robust for outlier-heavy. Required for GD / kNN / Ridge / Lasso / PCA. Not needed for trees. Log / power transforms come first if the feature is skewed.
- **The one rule:** fit any preprocessor on train data only. Wrap everything in a `Pipeline` and you can't accidentally violate it.

HW01c - practice

1. On the Yerevan rent dataset: detect the missingness pattern, choose a strategy, justify your choice in 2-3 sentences.
2. Build a `ColumnTransformer` for the numeric + categorical features. Fit Ridge regression in a single Pipeline. Report 5-fold CV MAE.
3. Deliberately leak: scale on full data, then on train-only. Compare CV scores and discuss why the leaky version looks better. *This is the most important question.*
4. Bonus 1: log-transform rent and re-fit. Report MAE in AMD (not log AMD) by inverting the transform with `np.expm1`.
5. Bonus 2: add a cyclic feature for `listed_at` hour-of-day. Does Ridge improve?
6. Bonus 3: replace Ridge with a tree-based model (e.g., `HistGradientBoostingRegressor`). Drop the scaler. Compare to the Ridge pipeline.