COMS4995W31
Applied Machine Learning

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Data

Week of AI - Data Edition

📉 The "Human Data" Crisis (Epoch AI Report)

- News: New research suggests we have exhausted 90% of high-quality public human text.
- Impact: Labs are aggressively pivoting to Synthetic Data generation (O-series reasoning chains) to train GPT-5/Avacado class models.

🍓 Reasoning Models & Inference-Time Compute

- Trend: The focus has shifted from "Pre-training Data" to "Inference Data" (Chain of Thought).
- Takeaway: Better data from user prompts is yielding higher ROI than retraining massive base models.

Agenda

- Motivation
- Data Cleaning
- Data Transformation
- Feature Engineering
- Feature Selection

Motivation

Why Data Matters 🤔

- Garbage in → Garbage out
- ML models are only as good as their data
- 80% of project time = data prep (industry stats)

Industry Insight: The "Strawberry" Paradox 🍓

The Question:

- Why did early LLMs (GPT-4 class) fail to count the 'r's in "strawberry"?

The Cause: It wasn't the model's logic; it was Data Representation.

- Tokenization: The model sees [Straw] + [berry], not s-t-r-a-w-b-e-r-r-y
- If the data input format destroys information, no algorithm can recover it

The Lesson:

- Data Representation dictates the upper bound of model intelligence
- (If the data is "blind" to individual letters, the model will be too)

Model Quality = Data Quality ⚖️

- Clean + consistent data → reliable predictions
- Poor + noisy quality data → misleading results

- ⚠️ Even the BEST algorithms **fail** with messy data

Real-World Dirty Data 🗃️

- Missing values → blanks, “N/A”
- Noisy values → typos, sensor errors
- Inconsistent formats → units, codes, duplicates

id	age	income	state	rating
1	25	80k	MARS	5
2	0	?	US-NY	N/A
3	-99	70,000	NY	4

The Hidden Killer: Duplicate Data 🗃️

The Problem:

- Internet data (Common Crawl) is full of duplicates

The Consequence:

- If a model sees the same sentence 50 times, it memorizes it instead of generalizing
- This leads to "Model Collapse" and severe overfitting

Industry Solution:

- **LSH (Locality Sensitive Hashing)**: Used by OpenAI & Anthropic to remove fuzzy duplicates at petabyte scale

Data Cleaning

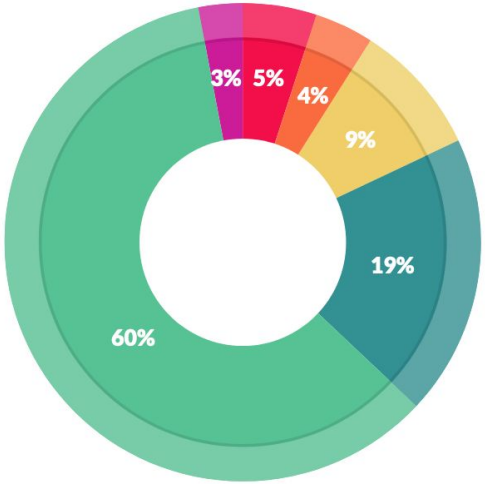
Why Clean Data? 🧹

- Dirty data → wrong insights
  - Inconsistent records can mislead the model, producing unreliable predictions
- 80% of ML effort = data preparation
  - Kaggle studies show the majority of project time is spent collecting, cleaning, and transforming data - not training fancy models
- Clean data = reliable models
  - Well-prepared datasets reduce bias, improve generalization

Why Clean Data?

How a Data Scientist Spends Their Day

Here's where the popular view of data scientists diverges pretty significantly from reality. Generally, we think of data scientists building algorithms, exploring data, and doing predictive analysis. That's actually not what they spend most of their time doing, however.



What data scientists spend the most time doing

- *Building training sets: 3%*
- *Cleaning and organizing data: 60%*
- *Collecting data sets; 19%*
- *Mining data for patterns: 9%*
- *Refining algorithms: 4%*
- *Other: 5%*

Types of Dirty Data 🚨

- Missing → empty values, “N/A”
  - Caused by skipped survey questions, sensor downtime, or data entry omissions
  - Leads to incomplete patterns and biased results
- Noisy → typos, random errors
  - Human mistakes (e.g., “25O00” instead of “25000”), faulty sensors
  - Adds variance and hides real signal
- Inconsistent → units, duplicates
  - Same info in different formats (lbs vs kg, “NY” vs “New York”)
  - Duplicate or conflicting records distort analysis

Missing Values - Simple Fixes 🧩

- Drop rows/columns (if sparse)
- Fill with constants (e.g., “Unknown”)
- Mean / Median / Mode imputation
- ⚠️ Imputation must be done on TRAINING DATA ONLY

Missing Values - Smarter Fixes 💡

- Class-wise mean/median
- Predictive models (regression, kNN)
- Add a “missing_flag” column

Noisy Data - Cause 🤔

- Faulty sensors
  - Hardware malfunction
  - Calibration drift
- Data entry mistakes
  - Copy-paste errors, wrong decimal placement
- Transmission errors
  - 👉 Example: temperature = -273 °C 😅

Handling Noisy Data 🔧

- Binning → smooth by mean/median
  - `data = bin(data).mean()`
- Regression smoothing
  - `data = fit_regression(x, y).predict(x)`
- Clustering → detect/remove anomalies
  - `anomalies = cluster(data) == outlier`

Inconsistent Data 🌀

- Example: USD vs RMB, lbs vs kg
- Schema mismatches (same field, diff names)
- Deduplication required
  - 👉 Visual idea: picture of “kg → lbs” conversion

Summary: Data Cleaning ✅

- Missing, noise, inconsistency = universal problems
- Strategies: drop, impute, smooth, normalize
- Domain knowledge + reproducibility are critical

Data Transformation

Why Transform Data? 🔄

- Raw data often not ready for models
- Transformation improves comparability & stability
- Visualization helps spot issues early

Normalization ⚖️

- Scale values into [0,1] range
  - Rescales each feature so the smallest becomes 0 and the largest becomes 1
- Useful for distance-based methods (kNN, clustering)
  - Ensures all features contribute equally to distance calculations; prevents large-scale features from dominating
- Sensitive to outliers
  - Extreme values stretch the range, making most data points compressed into a narrow band

Standardization 📏

- Transform data to mean = 0, std = 1
  - Centers each feature around zero and rescales by its standard deviation
- Works better for many ML models
  - Especially useful for linear regression, logistic regression, SVMs, and neural networks that assume standardized inputs
- Less sensitive to outliers vs normalization
  - Outliers still affect the mean/variance, but the effect is weaker than min–max scaling

Comparison

Aspect	Normalization ⚖️	Standardization 📏
What it does	Scale values into [0,1] range	Shift to mean = 0 and scale to std = 1
Effect	Compresses data into a fixed interval	Centers and balances features
Good for	Distance-based methods (kNN, clustering)	Linear/Logistic Regression, SVMs, Neural Nets
Outliers	Very sensitive (extremes dominate scaling)	Less sensitive, still influenced
Intuition	“Stretch/squash” to fit between 0–1	“Re-center & rescale” for comparability

Visualization for Cleaning 📊

- Histograms → spot missing values & skewed distributions
- Scatterplots → reveal outliers & correlations
- Boxplots → highlight anomalies within groups

Summary: Transform ✅

- Transform: normalize, standardize etc.
- Visualize: histograms, scatterplots, boxplots
- Goal: make data reliable, interpretable, ready for ML
  - 👉 Flow: Raw Data → Transform → Visualization → Insights


DATA

Feature Engineering

What is a Feature? 🔍

- Representation of raw data → input to algorithms
- Converts context into numbers
- Example:
  - 👉 “age” → bucket “young/middle/old”
  - 👉 [Visual] raw → feature transformation diagram

Why Feature Engineering? 🎯

- Expose structure hidden in raw data
  - Turn messy signals into meaningful patterns
  - e.g., timestamps → day of week, hour
- Improve model performance & interpretability
  - Well-designed features reduce noise, boost accuracy, and make results easier to explain
- Often more impactful than algorithm choice
  - A simple model with strong features can **outperform** a complex model with poor inputs

Categorical Features 🏷️

- One-hot encoding → binary vectors
  - Create a new column for each category, with 1 if the row belongs to that category and 0 otherwise
  - ✅ Preserves all categories without assuming order
  - ⚠️ Can lead to high-dimensional, sparse data if categories are many

Categorical Features 🏷️

- Target encoding → replace with mean target
  - Replace each category with the average value of the target variable for that category

  - ✅ Compact representation, powerful for tree-based models
  - ⚠️ Risk of leakage if target statistics are computed using the full dataset — must be done on training folds only

Encoding Comparison

Method	Example (`color`)	Pros 👍	Cons ⚠️
One-hot	Red → [1,0,0]	Simple, no leakage	High dimensional, sparse
Target encoding	Red → 0.72	Compact, powerful for trees	Risk of leakage if not careful

Text Features ✍️

- Tokenization basics: words, subwords
  - Break text into smaller units (e.g., “cats” → [“cat”, “##s”]); choice affects vocabulary size and coverage

- Bag-of-Words → high-dimensional & sparse
  - Represent documents by raw word counts
  - Easy to implement but ignores order and meaning

Text Features ✍️

- TF-IDF → weigh distinctive words
  - Scale word importance by frequency in document vs across corpus; highlights informative terms (e.g., “fraud” in reviews)

- Embeddings → semantic meaning (Word2Vec, BERT)
  - Map words into dense vectors where similar meanings cluster together; capture context, semantics, and relations

Industry Insights 💼

- Simple, domain-informed features often beat fancy models
- “Better data and features trump fancier algorithms — again and again.”
- Key takeaway:
  - Do NOT underestimate the power of simple and interpretable features

Summary: Feature Engineering ✅

- Features = bridge from data → ML
- Good features matter more than complex models
- Avoid leakage & redundancy

👉 Flow: Raw Data → Features → Model

Feature Selection

Why Select Features? ✂️

- Reduce overfitting
- Improve training speed
- Increase interpretability

Common Methods 🏗️

- Decision trees → built-in feature importance
    - Tree models (Random Forest, Gradient Boosted Trees) rank features by how much they reduce impurity
    - Naturally highlight the most informative splits
    - Importance scores can be biased toward high-cardinality features, so interpret with care

Common Methods 🏗️

- LASSO regularization → zero-out weak features
  - Adds an L1 penalty term to the loss function
  - Forces coefficients of less useful features exactly to zero, performing selection during training
  - Works well for high-dimensional, sparse data

Summary: The Data-First Mindset 🧠

Architecture is a Commodity, Data is the Moat

- In 2026, everyone has access to the same models
- Our competitive advantage is Proprietary, Clean, and Deduplicated Data

Representation is the Ceiling

- Remember the Strawberry Paradox: If your tokenizer (feature engineering) is blind, your model is blind
- Always visualize your data representation before training

Summary: The Data-First Mindset 🧠

The "Unsexy" 80% Rule

- Spending 80% of your time on Cleaning & Transformation is not "prep work" - it IS the work
- Simple features + Clean data > Complex algorithms + Dirty data

The New Standard

- Classical approach: "Fill missing values with mean."
- Modern approach: "Detect duplicates, generate synthetic patches, and fix representation"

Level Up: What to Ask Your AI Tutor 🚀

To deepen your understanding of today's lecture, try these prompts:

On Deduplication (The Industry Standard):

- "Explain how LSH works for deduplicating billion-scale datasets. Write a Python script to deduplicate a list of slightly similar strings."

On Modern Imputation:

- "Compare MICE (Multiple Imputation) vs. KNN Imputation for a housing dataset. When should I use one over the other?"

On Synthetic Data:

- "How can I use an LLM to generate synthetic rows to balance an imbalanced classification dataset? Give me a prompt example."