

Minor in AI

Revising Python Data Structures

1 The Building Blocks of Python: Why Data Structures Matter

Imagine you're a real estate analyst tracking housing prices. You need to store:

- Fixed property details (size, rooms) that **shouldn't change**
- Market prices that **can change** daily
- Quick access to prices by property type

This is where Python's data structures shine! They're like different types of storage containers:

Tuples: Locked boxes for permanent records

Lists: Flexible shelves for changing items

Dictionaries: Labeled drawers for quick access

In our case study, a builder refuses to negotiate prices. We'll use data structures to:

1. Store unchangeable property features and prices
2. Process data for price predictions
3. Compare different pricing models

2 Data Structures in Action: The Real Estate Case Study

2.1 The Problem: Immovable Prices

Our builder has fixed pricing:

- 1000 sqft, 2 rooms → 1,600,000
- 1200 sqft, 3 rooms → 1,900,000
- *(and more properties...)*

He insists: "**Prices are set in stone!**" How do we store this so no one accidentally changes prices?

2.2 Solution: Tuples within Lists

```
1 # Storing unchangeable property data
2 data = [
3     ((1000, 2), 1600000), # Property 1: (features), price
4     ((1200, 3), 1900000), # Property 2
5     ((1500, 3), 2200000), # Property 3
6     ((1800, 4), 2500000), # Property 4
7     ((2000, 5), 3000000)  # Property 5
8 ]
```

Code Breakdown

Understanding the structure:

- `data` is a **list** containing all properties
- Each property is a **tuple** with two parts:
 - (1000, 2): Features tuple (square feet, rooms)
 - 1600000: Price (single value)
- Why nested tuples?
 - Outer list: Can add/remove properties
 - Inner tuple: **Lock** features and prices

Try this: Attempt to modify a price with `data[0][1] = 1700000` - you'll get **TypeError** proving immutability!

2.3 Preparing Data for Analysis

```

1 # Step 1: Create empty containers
2 square_feet_list = []      # Will store all square footages
3 rooms_list = []           # Will store all room counts
4 price_list = []           # Will store all prices
5
6 # Extract data from nested structure
7 for item in data:
8     # Unpack: item = ((sqft, rooms), price)
9     features, price = item
10
11     # Unpack features: features = (sqft, rooms)
12     sqft, rooms = features
13
14     # Populate lists
15     square_feet_list.append(sqft)  # Add sqft to list
16     rooms_list.append(rooms)       # Add room count to list
17     price_list.append(price)       # Add price to list
18
19 # Step 2: Normalize data (scale to 0-1)
20 max_sqft = max(square_feet_list)  # Find largest sqft (2000)
21 normalized_sqft = [sqft/max_sqft for sqft in square_feet_list]
22 # Result: [0.5, 0.6, 0.75, 0.9, 1.0]
```

Code Explanation

Key operations:

1. `for item in data:` Loop through each property
2. `features, price = item:`
 - `item = ((1000, 2), 1600000)`
 - `features` → (1000, 2)
 - `price` → 1600000
3. `sqft, rooms = features:`
 - `features = (1000, 2)`
 - `sqft` → 1000
 - `rooms` → 2
4. `.append()`: Adds values to lists
5. `List comprehension`: `[sqft/max_sqft for ...]` creates new list by:
 - Taking each `sqft` in `square_feet_list`
 - Dividing by `max_sqft` (2000)

Why normalize? Equalizes scale - 2000 sqft won't dominate 5 rooms in calculations.

2.4 Making Predictions with Simple Models

```

1 # Prediction formula: Price = (sqft * w1) + (rooms * w2) + bias
2 weight_sqft = 250000 # Value per sqft
3 weight_room = 50000  # Value per room
4 bias = 5000          # Base price
5
6 def predict(feature_tuple):
7     """Predict price from normalized features"""
8     # Unpack: feature_tuple = (normalized_sqft, normalized_rooms)
9     sqft, rooms = feature_tuple
10
11     # Calculate prediction
12     predicted_price = (sqft * weight_sqft) + (rooms * weight_room) +
    bias
13     return predicted_price
14
15 # Create list of predictions
16 predictions = []
17 for item in normalized_data:
18     features, actual_price = item # Unpack data
19     pred_price = predict(features) # Get prediction
20     predictions.append(pred_price) # Store prediction
21
22 # Simplified alternative (list comprehension):

```

```
23 # predictions = [predict(features) for features, _ in normalized_data]
```

Predictor Breakdown

How prediction works:

- `def predict(...)`: Function definition
- **Parameters**:
 - `feature_tuple`: Normalized (sqft, rooms) like (0.5, 0.4)
- **Calculation**:

$$\begin{aligned} \text{Price} &= (0.5 \times 250000) + \\ &\quad (0.4 \times 50000) + \\ &\quad 5000 = 155000 \end{aligned}$$

- **Loop logic**:
 - Extract features from each property
 - Feed to `predict()` function
 - Store result in `predictions` list

Why weights? Represents how much each feature contributes to price. Here sqft (250000) matters more than rooms (50000).

2.5 Evaluating Models with Dictionaries

```
1 # Calculate accuracy metric
2 def simple_accuracy(true_prices, pred_prices):
3     """Compare actual vs predicted prices"""
4     total_error = 0
5
6     # Calculate sum of squared errors
7     for i in range(len(true_prices)):
8         error = true_prices[i] - pred_prices[i] # Difference
9         squared_error = error ** 2 # Square to magnify
10        large errors
11        total_error += squared_error # Accumulate
12
13    # Mean Squared Error (average error)
14    mse = total_error / len(true_prices)
15
16    # Convert to accuracy (higher is better)
17    accuracy = 1 / (1 + mse)
18    return accuracy
19
20 # Store model scores
21 model_scores = {} # Create empty dictionary
22
23 # Add Linear Model score
24 linear_acc = simple_accuracy(price_list, predictions)
```

```

24 model_scores["Linear Model"] = linear_acc # Store with key
25
26 # Add Constant Predictor (example)
27 model_scores["Constant Predictor"] = 0.42
28
29 # Find best model
30 best_model = max(model_scores, key=model_scores.get)
31 print(f"Best model: {best_model}") # Output: "Linear Model"

```

Dictionary Deep Dive

Step-by-step evaluation:

1. `simple_accuracy()`:

- `true_prices`: Actual prices [1600000, 1900000,...]
- `pred_prices`: Predicted prices [155000, 182000,...]
- `error`: Difference for each property
- `squared_error`: Makes large errors more noticeable
- `mse`: Average error across properties

2. Dictionary operations:

- `model_scores = {}`: Creates empty dictionary
- `model_scores["Linear Model"] = ...`: Stores value with key
- `max(..., key=model_scores.get)`: Finds key with highest value

Why dictionaries? Instant lookup: `model_scores["Linear Model"]` immediately returns accuracy without searching through lists.

3 Key Takeaways: Choosing Your Data Structures

Structure	Mutability	Best For	Real-World Analogy
List	Mutable	Changing collections (shopping lists)	Backpack - add/remove items freely
Tuple	Immutable	Fixed records (property details)	Engraved stone tablet - permanent
Dictionary	Mutable	Labeled data (model scores)	File cabinet - find things by name

Golden Rules:

- Use `tuples` when data **must not change** (like our builder's prices)
- Use `lists` when processing data (normalization, predictions)
- Use `dictionaries` for quick lookups (model comparisons)
- **Remember LTD**: Lists, Tuples, Dictionaries - the Python data trifecta!

Data Structure Superpowers

Operation	Champion Structure
Add/remove items	List
Protect from changes	Tuple
Find by name	Dictionary
Memory efficiency	Tuple

Pro Tip

When in doubt:

1. Need to change data? → [List](#)
2. Need to preserve data? → [Tuple](#)
3. Need to find data by name? → [Dictionary](#)