Real Estate

Automated Valuation Model

Jeremy Wizenfeld, Aaron Poulad, and Yair Levie

Problem:

BUSINESS | EARNINGS

Zillow's Shuttered Home-Flipping Business Lost $881 Million in 2021

Real-estate company says in a letter to shareholders that it is targeting revenue of $5 billion by 2025

By *Will Parker* Follow

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- Given the rapid pace of real estate markets, manually evaluating numerous properties can be time-consuming and inefficient.
- iBuying- a company makes an offer to buy a home without going out to visit it
- Successful in generic houses of similar quality and size, but less effective for high-end or low-quality homes where construction quality significantly impacts pricing.
- Zillow's Shuttered Home-Flipping Business Lost $881 Million in 2021

Solution:

- Examine property images to refine price prediction
  - Allows us to account for building **quality**, not seen in standard property data
- Convolutional Neural Network (**CNN**) approach
  - Use a CNN to categorize room types and score key **visual features** such as property condition, style, and quality from specific rooms
- Score refinement
  - Consolidate multiple image scores into an **overall property quality score**, and combine with structured data to attain a more accurate property value estimate

Project Timeline

Q1:
August 28th-September 25th

1. Researched CNNs

2. Researched Regression Models

3. Devised a plan for data collection

Q2:
September 26th-October 14th

1. Deployed Label System on GCP to Collect and Clean Data

2. Developed basic Linear Regression models

Q3:
October 15th-November 20th

1. Created CNN for image classification and scoring

2. Linear Regression implemented the image scores

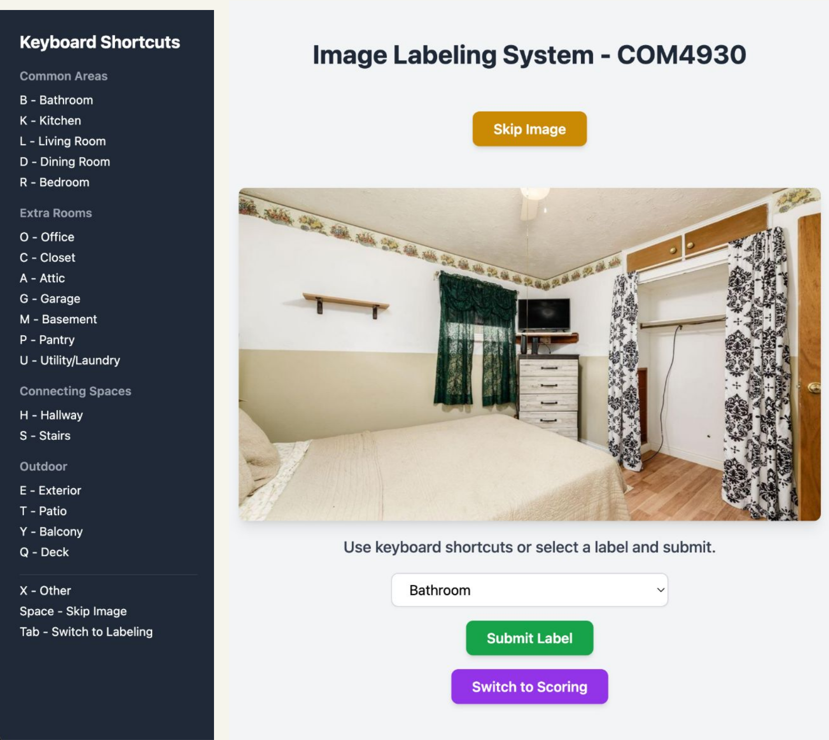
3. Pipeline to pull from Zillow API

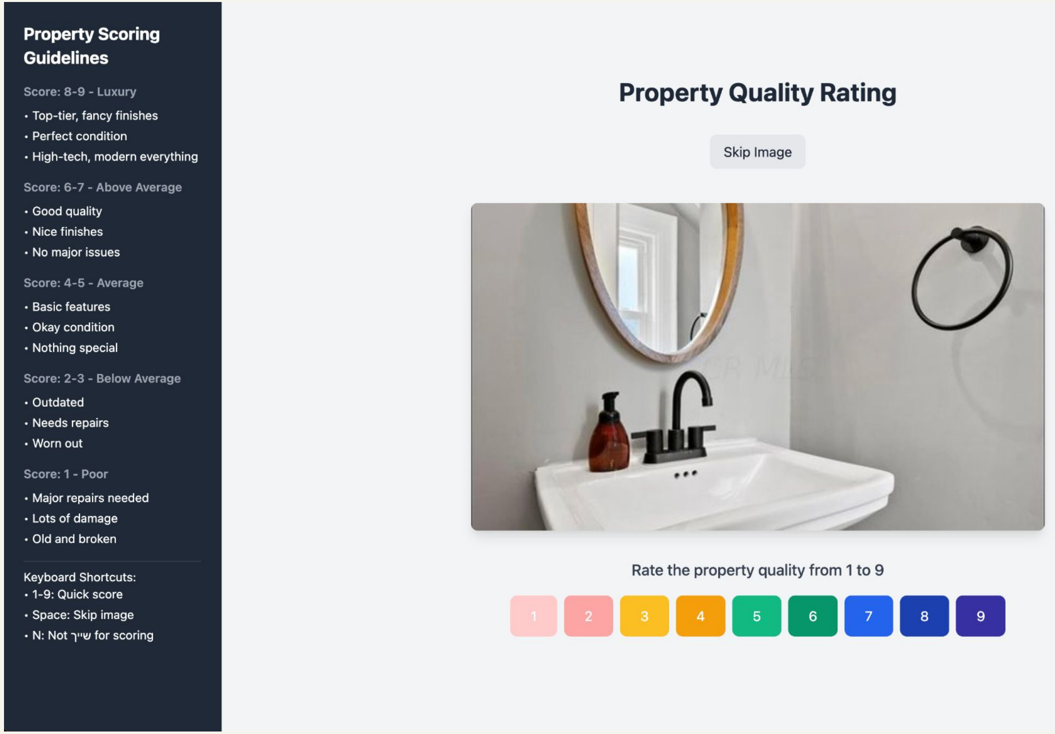
Q4:
November 21st-December 11th

1. Merged all components and fixed bugs

2. Built a UI to input address and quickly receive prediction

Data Collection: Labeling and Scoring





CNN

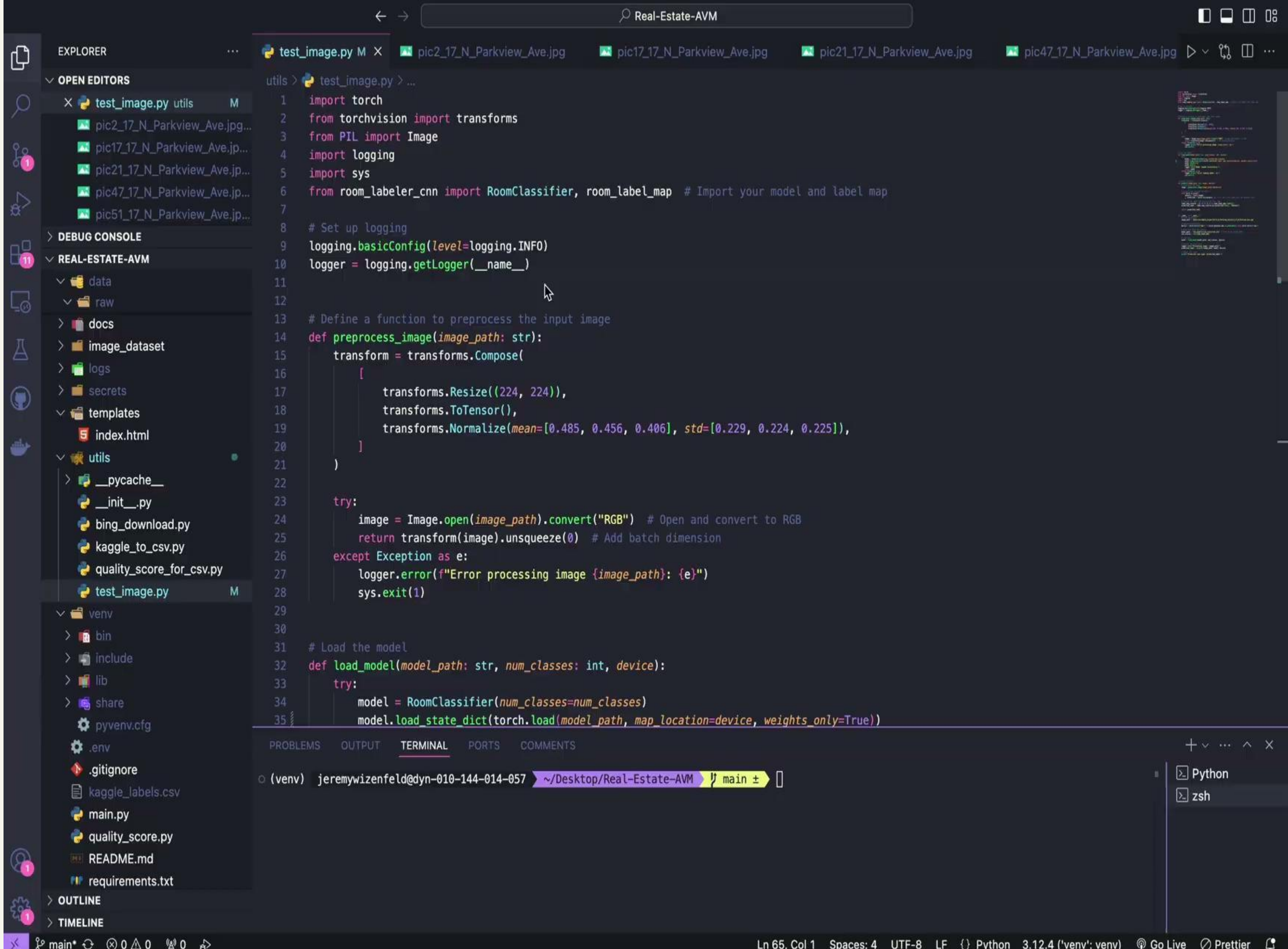
ResNet18-Based Room Classifier (11,181,642 parameters)

- **Task**: Multi-class classification (predict room type among 10 categories).
- **Architecture**:
  - Pretrained ResNet18
  - Final fully connected (FC) layer replaced with `nn.Linear(in_features, num_classes=10)`.
  - Retains strong feature-extraction capacity from ImageNet pretraining.
- **Loss Function**:
  - `nn.CrossEntropyLoss` for multi-class classification.
- **Optimizer & Scheduler**:
  - Adam optimizer with a learning rate of 0.001.
  - `ReduceLROnPlateau` scheduler to adjust learning rate when loss plateaus.

MobileNetV2-Based Score Regressor (2,305,921 parameters)

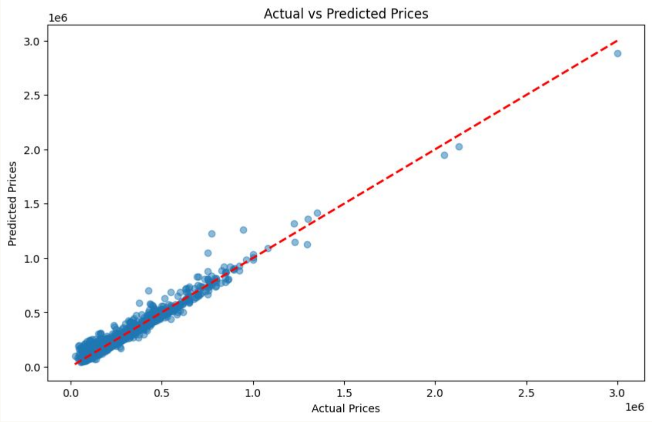
- **Task**: Regression (predict a continuous “score”).
- **Architecture**:
  - Pretrained MobileNetV2 (smaller version of ImageNet, training was taking too long).
  - Final classifier replaced with a small FC “head”:
    - `nn.Dropout(0.2)` > `nn.Linear(...)` > `nn.ReLU()` > `nn.Dropout(0.2)` > `nn.Linear(..., 1)`
  - Lightweight and efficient, suitable for large-scale or MPS (Metal Performance Shaders) usage.
- **Loss Function**:
  - `nn.MSELoss` for regression tasks.
- **Optimizer**:
  - Adam optimizer with a learning rate of 0.001.

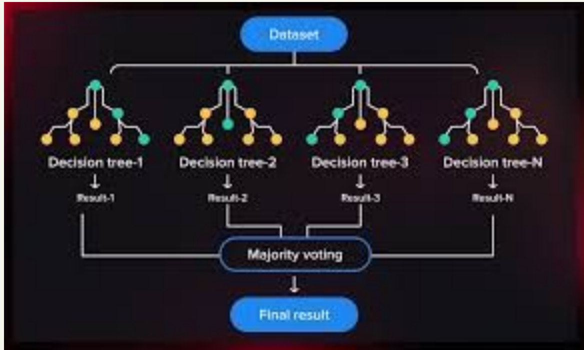
Label CNN Demo



Price Prediction Model

- **Linear Regression**
  - Finds linear relationships between features and price
- **Decision Tree**
  - Partitions data into regions based on feature values and averages price within those regions
- **Random Forest**
  - Creates multiple decision trees and averages them, being less sensitive to overfitting
- **Gradient Boosting (XGBoost)**
  - Error correction on top of random forest, and can handle complex relationships and interactions in the data.





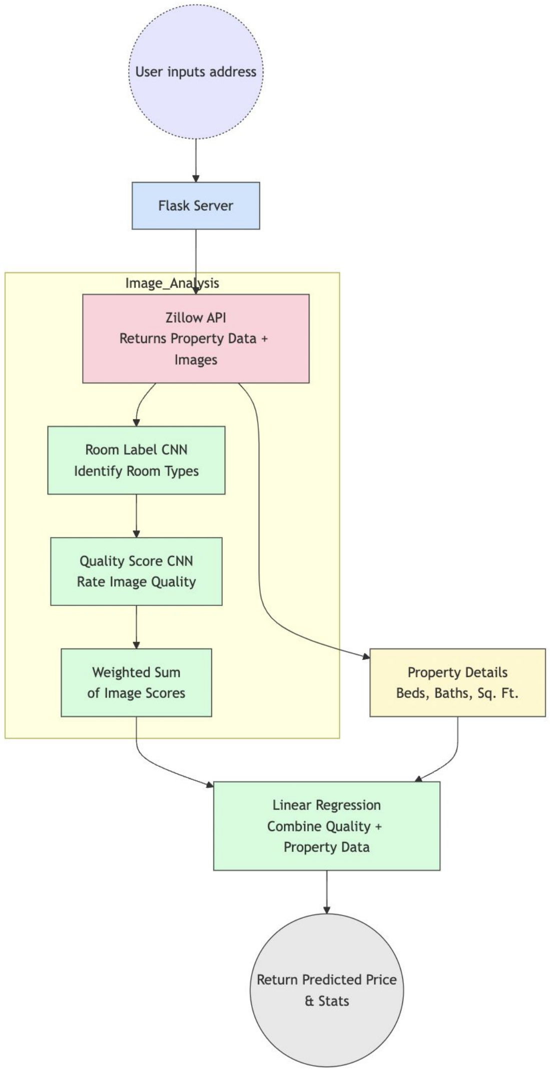
Results

Data incorporated	MAE	RMSE	SMAPE	R^2
Only elementary data	$50,931	$82,732	18.73%	86.50%
With Zestimate	$30,183	$52,946	12.71%	94.47%
With image scores	$29,647	$52,171	12.74%	94.63%
Zestimate accuracy	$34,910	$61,141	14.32%	93.28%

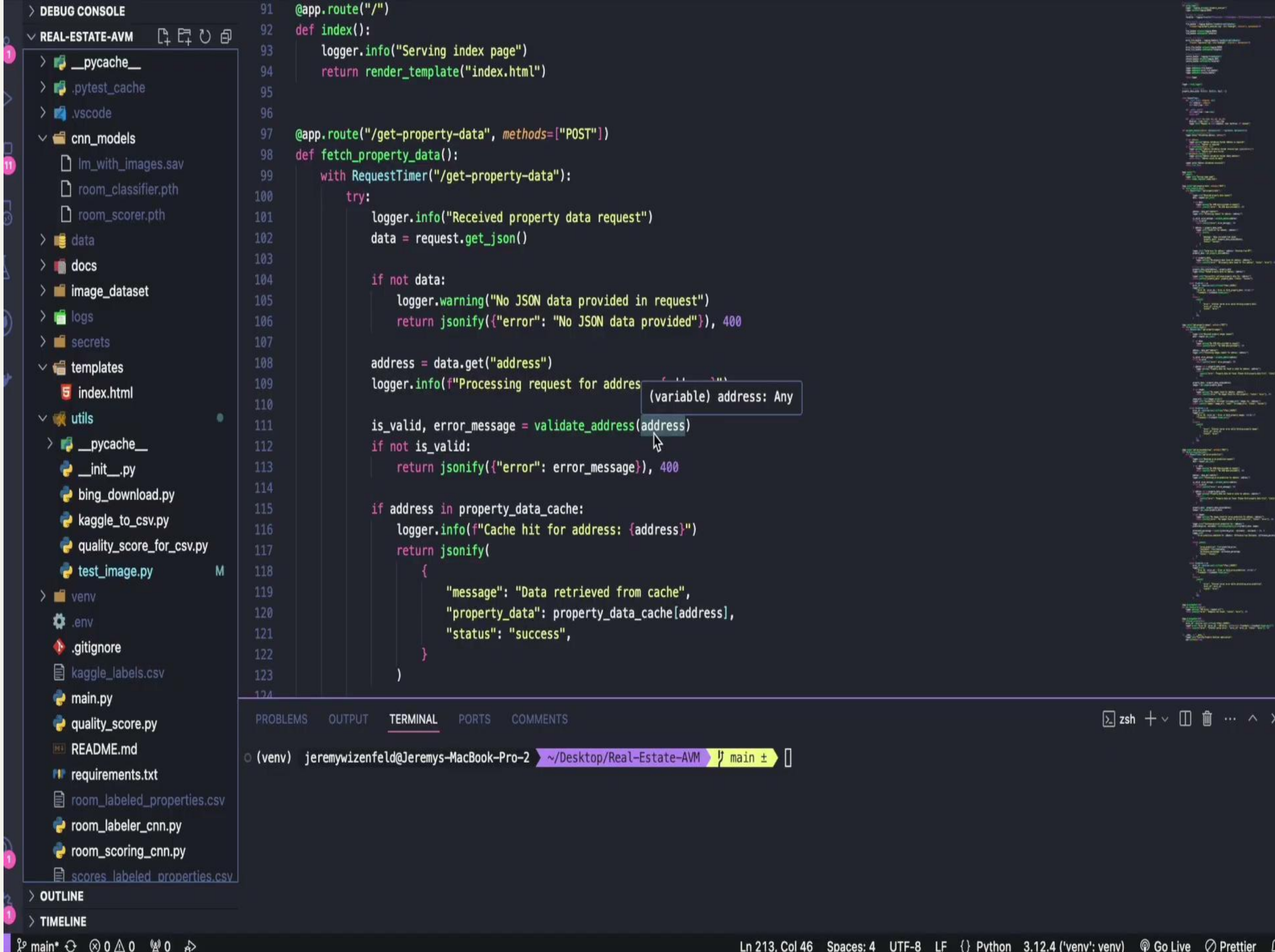
Data used for all stages: bathrooms, bedrooms, living area, lot size, tax assessed value, yearBuilt
Trained on 5441 properties; tested on 1361.

Putting It All Together

1. **User Input**: The user enters a property address.
2. **Data Retrieval**: A Flask server queries the Zillow API to fetch property details (e.g., beds, baths, square footage) and corresponding image URLs.
3. **Room Classification**: Each image is passed through a *Room Label CNN* to identify the type of room (kitchen, bedroom, etc.).
4. **Image Quality Scoring**: The images are then fed into a *Quality Score CNN*, which assigns a quality rating based on visual and aesthetic criteria.
5. **House Quality Score**: The individual image scores are combined (weighted sum) into an overall “house quality” metric.
6. **Price Prediction**: A *Linear Regression* model uses both the property’s features (e.g., size, location) and the house quality score to estimate the final home value.
7. **Results**: The predicted price, along with relevant statistics, is sent back to the user interface.



Demo


DEBUG CONSOLE
REAL-ESTATE-AVM
__pycache__
.pytest_cache
.vscode
cnn_models
lm_with_images.sav
room_classifier.pth
room_scorer.pth
data
docs
image_dataset
logs
secrets
templates
index.html
utils
__pycache__
__init__.py
bing_download.py
kaggle_to_csv.py
quality_score_for_csv.py
test_image.py
venv
.env
.gitignore
kaggle_labels.csv
main.py
quality_score.py
README.md
requirements.txt
room_labeled_properties.csv
room_labeler_cnn.py
room_scoring_cnn.py
scores_labeled_properties.csv
OUTLINE
TIMELINE
@app.route("/")
def index():
logger.info("Serving index page")
return render_template("index.html")
@app.route("/get-property-data", methods=["POST"])
def fetch_property_data():
with RequestTimer("/get-property-data"):
try:
logger.info("Received property data request")
data = request.get_json()
if not data:
logger.warning("No JSON data provided in request")
return jsonify({"error": "No JSON data provided"}), 400
address = data.get("address")
logger.info(f"Processing request for addres
(variable) address: Any
is_valid, error_message = validate_address(address)
if not is_valid:
return jsonify({"error": error_message}), 400
if address in property_data_cache:
logger.info(f"Cache hit for address: {address}")
return jsonify(
{
"message": "Data retrieved from cache",
"property_data": property_data_cache[address],
"status": "success",
}
)
PROBLEMS
OUTPUT
TERMINAL
PORTS
COMMENTS
zsh
(venv) jeremywizenfeld@Jeremys-MacBook-Pro-2
~/Desktop/Real-Estate-AVM
main ±
main*
Ln 213, Col 46
Spaces: 4
UTF-8
LF
Python
3.12.4 ('venv': venv)
Go Live
Prettier

Future Improvements

Crowdsourced Quality Scores
Gather user-based ratings from many more properties to refine the **Quality Score**. A larger dataset would improve both accuracy and confidence in the predicted price.

Geolocation & Comps
Incorporate geospatial data to identify recently sold homes nearby. **Comparable Sales (Comps)** data can be automatically fed into the model to better reflect local market conditions.

Economic Indicators
Pull in **macroeconomic data** (e.g., interest rates, GDP trends) so the model can adjust dynamically for broader market shifts—a key lesson from Zillow’s 2021 iBuying challenges.

Model Fine-Tuning
Experiment with different **weights for room scores** and **hyperparameters** (e.g., learning rates, number of layers) to further optimize accuracy and reliability.

Technologies