

Real Estate Investment Opportunity Image Classifier

Capstone Final Report | Shawn Munir

Summary

With over 80% accuracy, the algorithm can tell whether a property is a candidate for investment from a single image alone.

The Problem

A real estate investor looking to flip a property, either to sell or to rent out, wants to know the opportunities. As with many things, however, there really is no alternative to human judgement. But that requires manually sifting through listings. Even with filters and email alerts, there aren't generally filters for 'investment opportunity,' i.e. something that is in fair condition, just outdated. A person can tell this instantly upon looking at images. And with the right training, so can a computer, with machine learning. That's where my algorithm comes in. This would open up the opportunity to set up filters and get notifications *specifically* for investment opportunities, whether to be incorporated into a website, or for one's personal use via an API/web scraping.

The matter has been greatly simplified as a start to a deeper endeavor, focusing on the greatest 'bang for the buck.' The idea was to make it as easy for the classifier to be trained as possible, thus, the types of images were very focused. Only images of the kitchen were used. The reasoning is that much – perhaps *most* – about the condition of a home and thus 'investability' can be reasonably inferred from the kitchen alone. This follows the assumption that, generally, if a kitchen is not updated, most of the rest of the home probably isn't either. But even if it is, just improvement of the kitchen alone would greatly boost resale value. The style cues of the kitchen generally extend into the dining and living areas in most spaces, thus representing a large portion of a property interior. It is usually very obvious in images whether a place is fully updated, even if just looking at *one* image, like of the kitchen. The kitchen is a good candidate too because of the recognizable components of counters, cabinets and often an island. If the kitchen *is* updated, there's a good chance much of the rest of the house is. The basic principle is that if the kitchen is updated, ignore it because this is likely not a worthwhile investment if the intention is to flip, and if the kitchen isn't updated, this property definitely has potential.

Further making training easier for the classifier, the 'styles' of the kitchens used were kept very consistent, as a starting point. If it can perform well there, then additional styles can be incorporated. Only two labels were used, but more can be made to specifically train and thus identify different styles, that can still be lumped together for binary end labels/decisions.

Additionally, this does not look at ANY tabular data like location, price, taxes, etc. These are already ready available for listings and thus a user can easily incorporate these as filters if they

wish. Further features can utilize this data to estimate with potential RESALE value / rent estimation assuming certain renovations and offerings, and also, with more advanced training, can estimate the costs too and thus profitability to really make an attempt at automating the real estate property investment opportunity financial evaluation. A whole report can even be generated, with AI images of the 'after'. Maybe even good guesses at what the *rest* of the home looks like based on extrapolating from just the kitchen, as AI image generators may do!

Again, there is no substitute for human judgement, however, with the amount of time and effort this could save, this could be the next best thing. The goal is to make the computer see with *our* eyes. We are replicating our eyes, comprehension and resultant behavior in the form of an algorithm.

[Charts, Figures]

Approach

A deep learning / neural network template was used. The original use was for classifying whether to flip a digital page or not. The parameters were tweaked

Many of the images used were from a related project from Ahmed & Moustafa in which images and tabular data were combined to predict real estate prices.

The truth labels are of course made with a human's subjective judgement. Thus, it should be made clear that the hope is for / success is for the algorithm to *match* our judgement. Everyone is slightly different, though, so 'truth labels' are subjective and so may vary slightly depending on who is labeling. But it is believed to be largely agreed upon. It is identifying what appear to be good *opportunities*, or candidates. Of course, there's no way to really know whether it will be a success, or even whether we'd actually be interested in buying the property until a proper, thorough in-person inspection is done. But this is a 'screener' that should capture most of the properties that the person themselves would want to look at further. It will miss a few, and will misidentify some, but for the amount of time and effort it saves due to automation, it is well worth it.

Making a decision to buy an investment property or not boils down to 4 steps:

1. finding an opportunity, which requires seeing images
2. run the numbers
3. evaluate in person
4. re-run numbers accordingly

This algorithm helps you with everything but #3, however, it can *get you there* much faster than typical methods. #1 is by far the most critical and most difficult

Note, similar results could also be achieved simply by targeting a certain price point that would likely only include things that are outdated, but this can be used to supplement that for added reassurance, as well as scanning for key terms in description such as “invest” and “flip”.

For a property to truly be a viable investment opportunity, the asking price and likely *selling* price is undoubtedly a factor, as that impacts profitability. Thus, it is assumed that this will be worked in and be a filter. Again, this algorithm is one key cog in a suite of moving parts; it's a starting point, a key member of the virtual real estate investor TEAM.

Model

A Sequential model is used, which is a layered neural network that can be used for classification. The output is a continuous value between our binary 0/1, which translates to the predicted probability that the user would deem this an flipping opportunity to look into. A simple decision line of .5 was chosen. To see the many other tunable parameters, see 'model metrics' text file.

Recommendations

1. Turn this classifier into a filter that users, investors and agencies/brokerages can toggle and include in their saved searches/alerts
2. Pair and expand upon this technology by incorporating tabular data and getting profitability/cost analysis and AI image generation for automated reports, saving the customer time and effort in this other phase of property investment evaluation
3. Further expand on this algorithm by incorporating images of other aspects of the house