

Model	Strategy	Target variable	Combination method
Model 1	A: Multi-kernel learning	Price	Linear weighting
Model 2	B: Multi-view concatenation by feature extraction	Price	Concatenation
Model 3	B*: Multi-view concatenation by boosting	Error term	Boosting
Model 4	C: Hybrid multi-view neural network	Price	Fusion by concatenation
Model 5	C*: Multi-view neural network	Price	Fusion by concatenation

Table 2: Summary of the different models compared.

used was not entirely complementary (in other words: overlapping) to the housing attributes, which also contain location information. In the work of ? (?), visual aesthetics extracted from the interior images might have improved predictive performance, because these features were not captured by the relational attributes. Second, using not only an independently and identically distributed hold-out set, but an out-of-sample test set further increases the required maturity level of the algorithm. On the in-sample validation dataset, the performance improved on RMSE and MAE. Nevertheless, on the out-of-sample predictions, only a lower RMSE could be reported (Table 3). As the RMSE penalizes larger errors stronger, it seems that extreme deviations are reduced. Though, the higher MAE could be caused by noise introduced by CNN’s prediction of the residual. Finally, models 4 and 5, both based on the multi-view neural network strategy, performed best by far. Model 4, the interpretable hybrid model provided 7.6% more accurate predictions in terms of MAE. Model 5, the more complex black-box model, outperformed the baseline by 13.4% in MAE. In the next section we show the possibilities to interpret models 3 and 4.

## 4.2 Interpretability of Multi-View Real Estate Appraisal Models

We report a selective set of coefficients of model 3 and model 4 in Table 4. While the constants differ between the models, the estimated effect of the size measured in square feet, the amenity fireplace or the location in Asheville have approximately the same size in both models. For example, the house price increases by approximately 5% when the house has a fireplace, *ceteris paribus*. As the continuous variables are min-max normalized, inferential statements cannot be made. Nevertheless, the sign and size of the coefficients show the direction and strength of impact on the house price. For example, the condition unsound is associated with a negative price influence, while having additional

half-bathrooms adds value to the real estate. From interpreting the coefficients magnitude, we can conclude that location aspects captured by the satellite image have a strong influence on the appraisal value, as the satellite image is among the top-3 largest coefficients for model 3 and top-15 for model 4. The difference between the magnitude of the image data coefficient of model 3 and 4 can be explained by the different scales of the variables. While model 3 includes the impact of the satellite image by the predicted residual and is thus measured in log-USD, model 4 learned the impact of the image implicitly. When the predicted residual changes by 1%, the house price changes by 1.05% (model 3). Furthermore, model 3 has the advantage that besides the coefficients, also standard errors, t-values, and significance levels can be extracted from the linear regression models learned during the experiment (Table 5). Statistical measures can be used to compare the coefficients of the different models. The magnitude of the coefficients and the standard errors of the coefficients (Strategy C and C\*) are lower, however, their performance seems to depend strongly on the weighting of the kernels. We suggest using these models as an advanced baseline, in addition to classic hedonic pricing models. Furthermore, models based on multi-view concatenation (Strategy B) seem to reliably increase predictive performance. This strategy is easier to optimize compared to multi-view neural networks, however, selecting the right (intermediate) target seems to be essential for successful learning. Moreover, it seems that the boosting approach of ? (?) (Strategy B\*) is more beneficial when the additional view is largely complementary to the other view. Nevertheless, the strength of this approach lays in interpretable coefficients and a statistical measurement of the effects. Consequently, this strategy seems very suitable for research contexts. From our experience, multi-view neural networks (Strategy C and C\*) perform best. It seems that learning a latent subspace leads to an effective feature representation even if the multiple views overlap in some features. In our experiment, the lo-

Model	MAE	RMSE
Baseline	40,303	71,518
Model 1	49,019	78,983
Model 2	38,395	61,663
Model 3	43,173	68,362
Model 4	37,225	61,429
Model 5	34,890	56,099

Table 3: Performance of the different models. Before evaluation, the log-transformation is inverted to gain better interpretability.

Variable	Model 3	Model 4
Constant	11.07	0.27
Square Feet	0.98	1.00
Year Built	0.34	0.53
Half Bathrooms	0.12	0.12
Fireplace	0.05	0.05
Style 1.5 Conventional	0.05	0.04
Locality Asheville	0.17	0.11
Condition Unsound	-0.23	-0.33
Satellite Image	1.05	0.41

Table 4: Selective set of coefficients of model 3 and 4

Strategy	Benefit	Disadvantage	Suggested use
A	Low training complexity	Lower accuracy	Advanced baseline model
B	Sequential training process	Difficult target variable selection	Alternative for strategy C
B*	Statistical interpretation	Complementary views required	Research purposes
C	Interpretability	High complexity of training	Multi-use
C*	Performance	High complexity of training	Predictive model

Table 5: Summarization of benefit and disadvantage of the different strategies

cation of the house is, in addition to the satellite image, also partly captured by city dummy variables. On the downside, according to ? (?), it can become difficult to achieve convergence of the neural network model, which raises the complexity of training. In addition, model 5 (Strategy C\*) comes as a black-box model. To mitigate this weakness, a semi-transparent multi-neural network as suggested by ? (?) can enhance interpretability. Nonetheless, it comes with an interpretability-accuracy trade-off, as model 4 has weaker predictive performance than model 5. We suggest using the multi-view neural networks for predictive models in applications where explainability is not a key objective.

## 5 Conclusion

Of course, our work is not without limitations. We have not yet investigated the interrelations between the structured housing attributes and the satellite images. Future research could, for example, analyze which information is overlapping between views and which information can only be captured by one or the other view. Another limitation is related to our data source. We use only a single dataset of Asheville, NC to assess the effect of the learning strategy on predictive performance. As related literature typically refers to neural network architecture search, future research should perform replication and ablation studies to examine, if results can be reproduced across datasets, image types and domains (beyond housing).

Despite these limitations, the following implications for research and practice can be derived from our findings. Satellite images can clearly improve the accuracy of computer-assisted mass appraisal. Our results indicate that the MAE can be reduced by up to 13%, depending on the chosen multi-view learning strategy. Therefore, banks and lenders should consider using visual data to improve their real estate appraisal estimates. Moreover, different techniques match different purposes and user groups. Researchers interested in a statistical interpretation of the results might find the boosting strategy of model 3 more appealing. Practitioners mainly interested in predictive accuracy might prefer model 5, the multi-view neural network.

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