



Predicting Bone Age Using Deep Learning

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Bone Age

Interpretation of skeletal maturity based on radiographic imaging

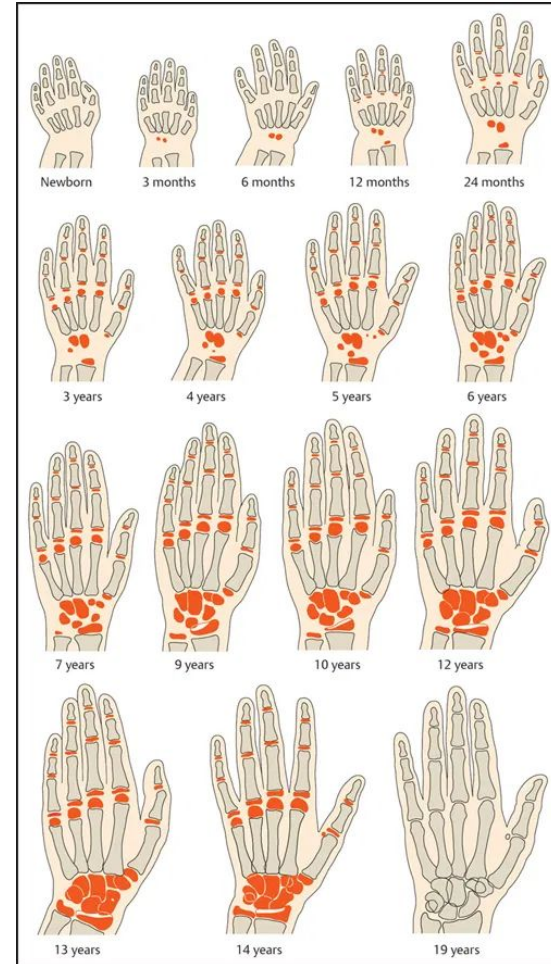


Image source: <http://www.rajen.net/boneage.html>

Bone Age: Use Cases



Clinical Uses



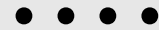
Diagnosis of growth disorders

Determining & monitoring
treatment

Prognosis



Non-Clinical Uses



Athletics

Forensics

Legal/Policy

Bone Age: Use Cases



Clinical Uses



Diagnosis of growth disorders

Determining & monitoring
treatment

Prognosis/adult height



Non-Clinical Uses

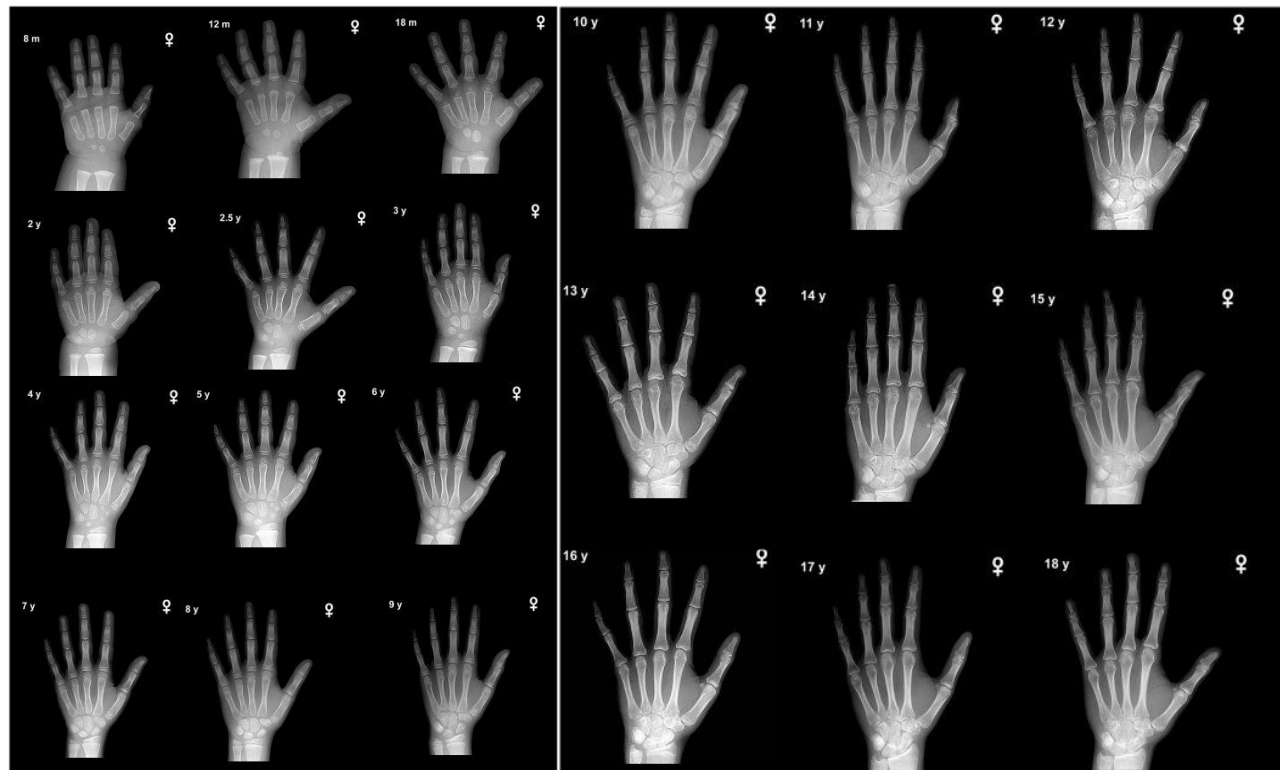


Athletics

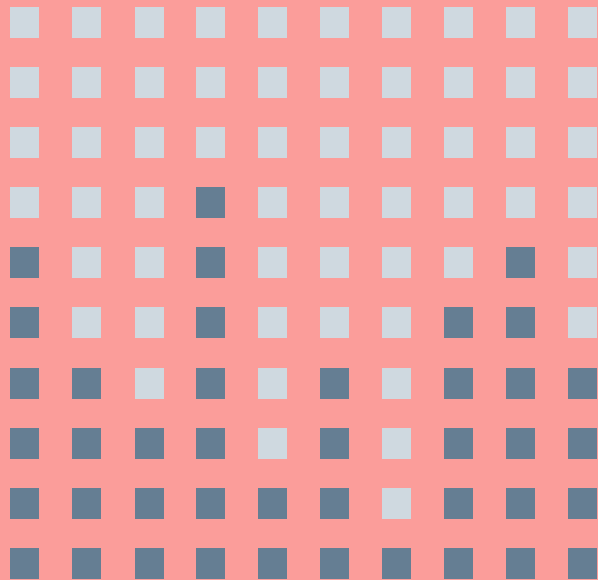
Forensics

Legal/Policy

Bone Age



Objective



Determine which factors
may be important to
consider in using
deep learning to predict
bone age

An abstract graphic on the left side of the slide, consisting of a network of light gray lines and dots. The lines form a complex, interconnected web of paths, with dots placed at various nodes along these paths, resembling a stylized circuit board or a data network map. The pattern is denser on the left and fades out towards the right.

Process

Data

RSNA Pediatric Bone Age Challenge 2017
dataset

14,236 X-rays

1-228 months

54% M, 46% F

Images provided by: Stanford University,
University of Colorado, UCLA

Data

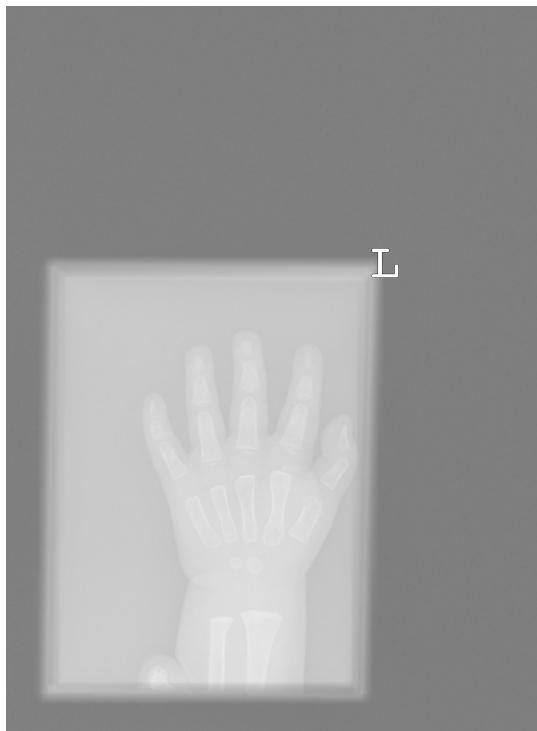
RSNA Pediatric Bone Age Challenge 2017
dataset

14,236 X-rays

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Modeling



Data

Augmentation

Enhancement

Resampling

Modeling



Data

Augmentation

Enhancement

Resampling



Transfer Learning

Pre-trained CNN:
Xception

Fine-tuning

Modeling



Data

Augmentation

Enhancement

Resampling



Transfer Learning

Pre-trained CNN:

Xception

Fine-tuning



Sex

Separate models

As feature

Modeling



Data

Augmentation

Enhancement

Resampling



Transfer Learning

Pre-trained CNN:
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Fine-tuning



Sex

Separate models

As feature



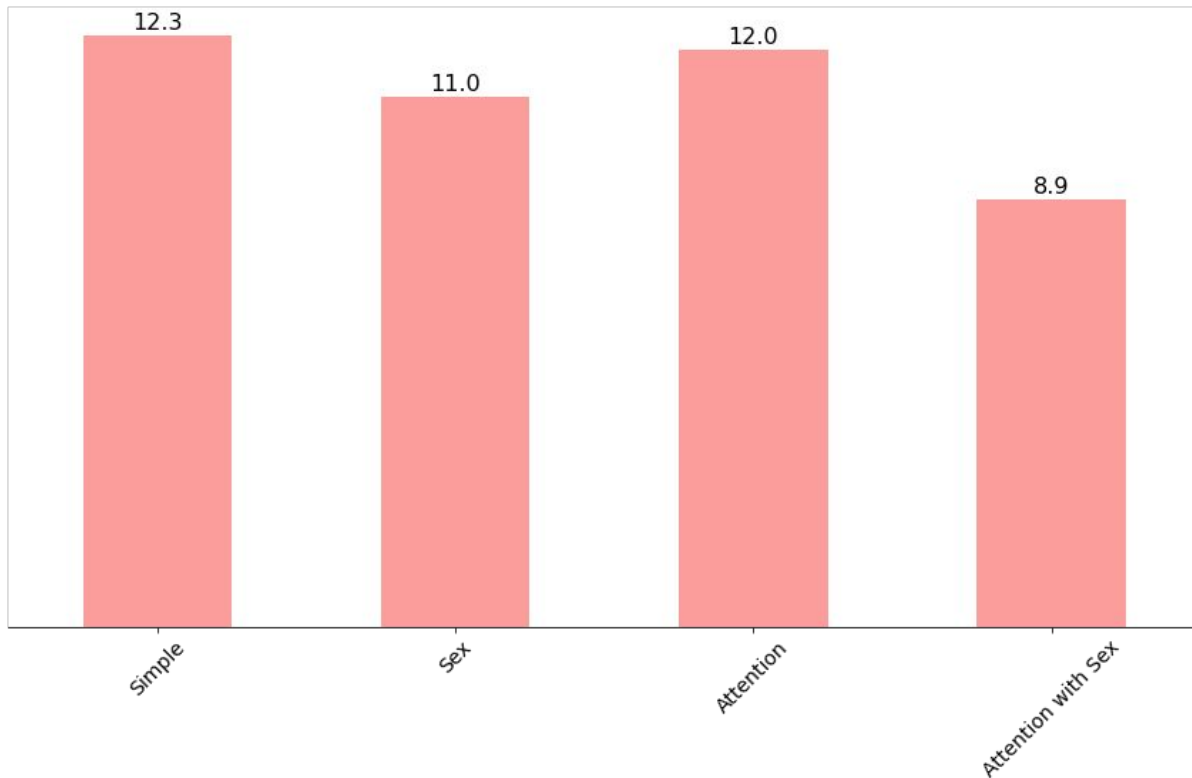
Attention Mechanism



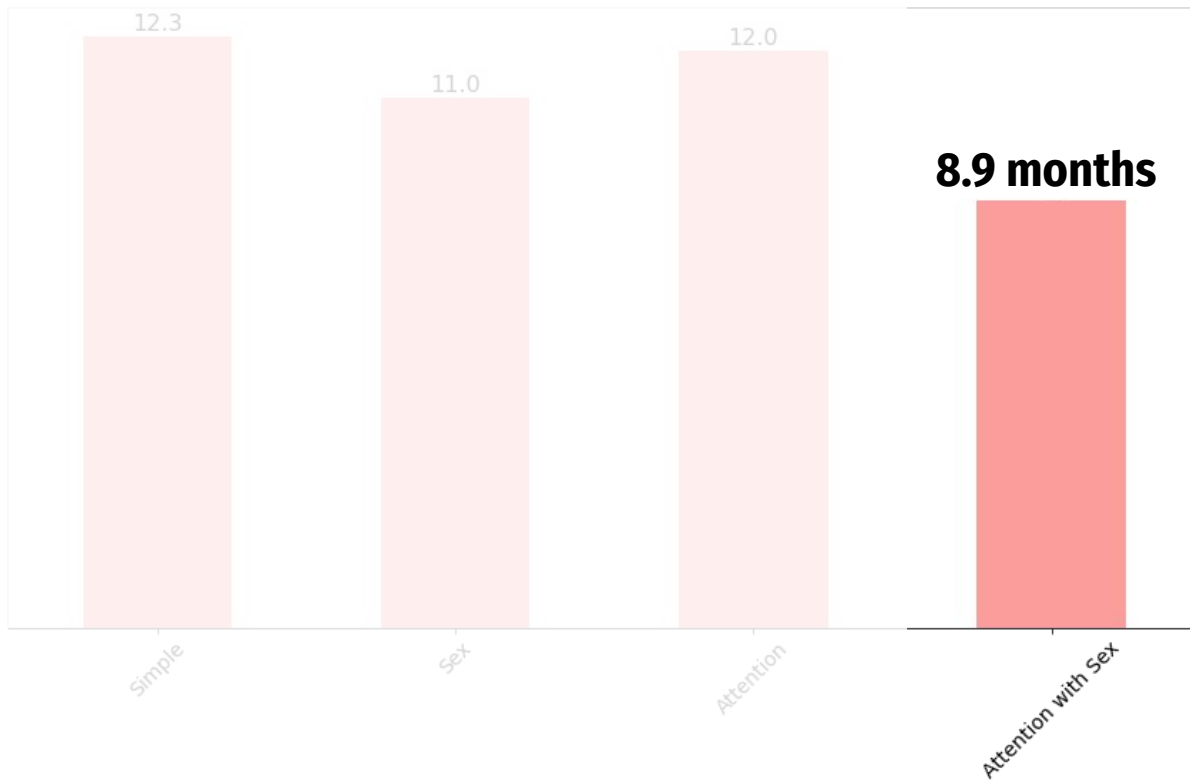
An abstract graphic on the left side of the slide, consisting of a network of light gray lines and dots. The lines form a complex, interconnected web of paths, with many small circles (nodes) placed at various points along these paths. The overall shape of the graphic is roughly triangular, pointing towards the top-left corner.

Models

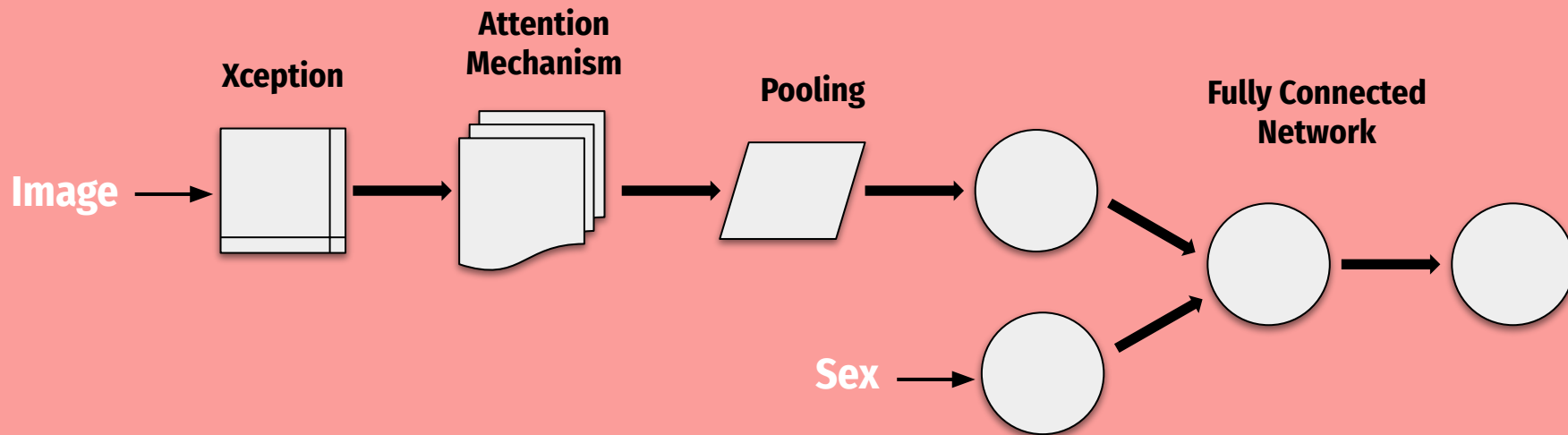
Comparison of Models: MAE (Months)



Best Model



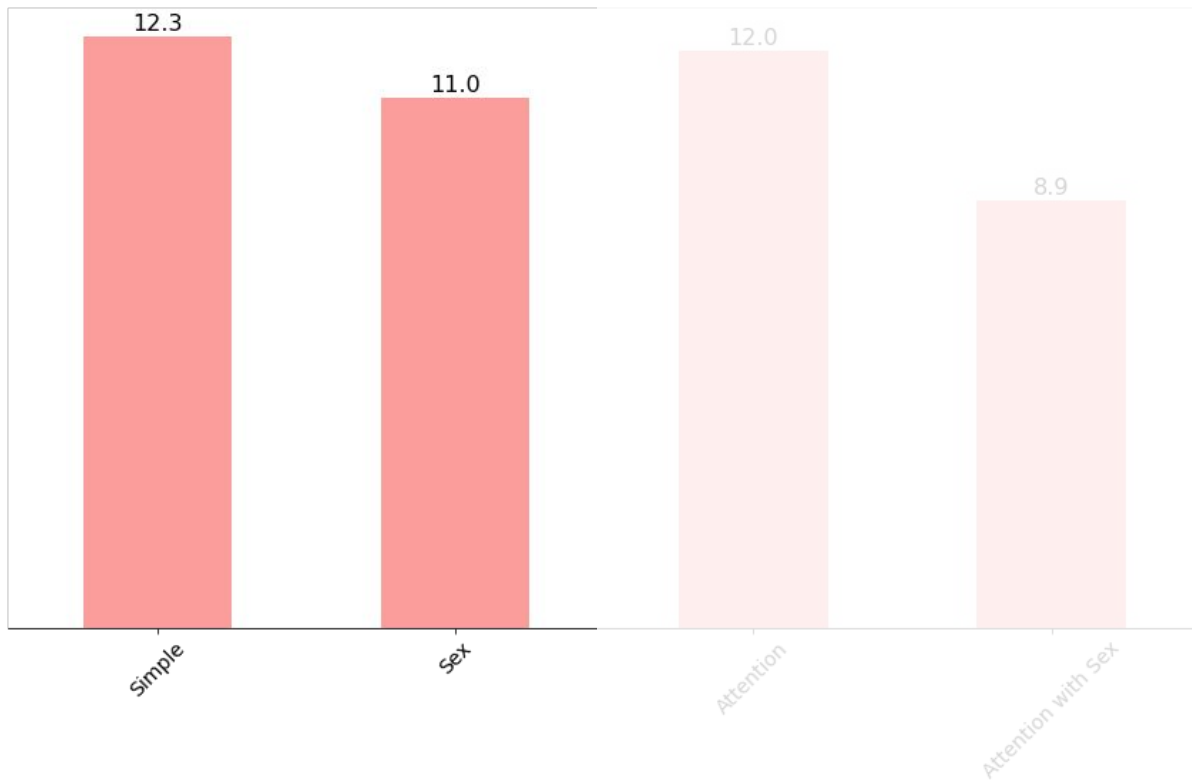
Best Model



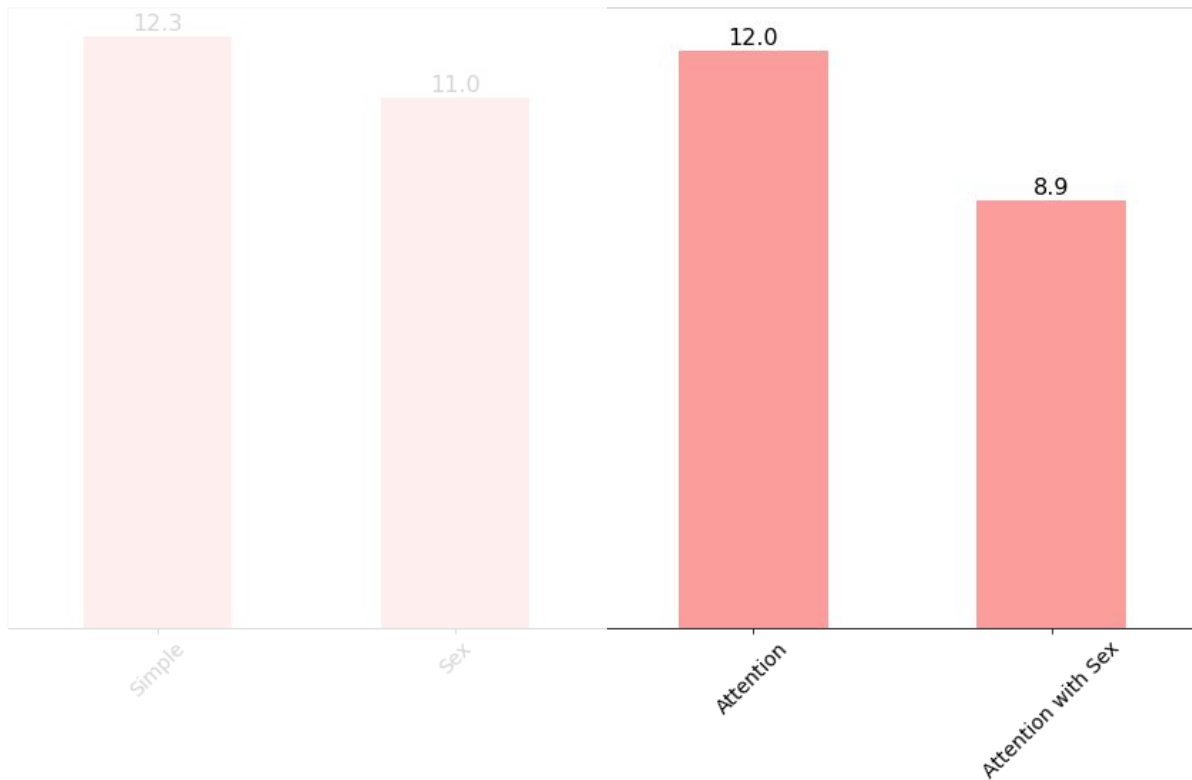
An abstract graphic on the left side of the page, consisting of a network of light gray lines and dots. The lines form a complex, interconnected web of paths, with many small circles (nodes) placed at various points along these paths. The overall shape of the network is roughly triangular, pointing towards the top right.

Insights

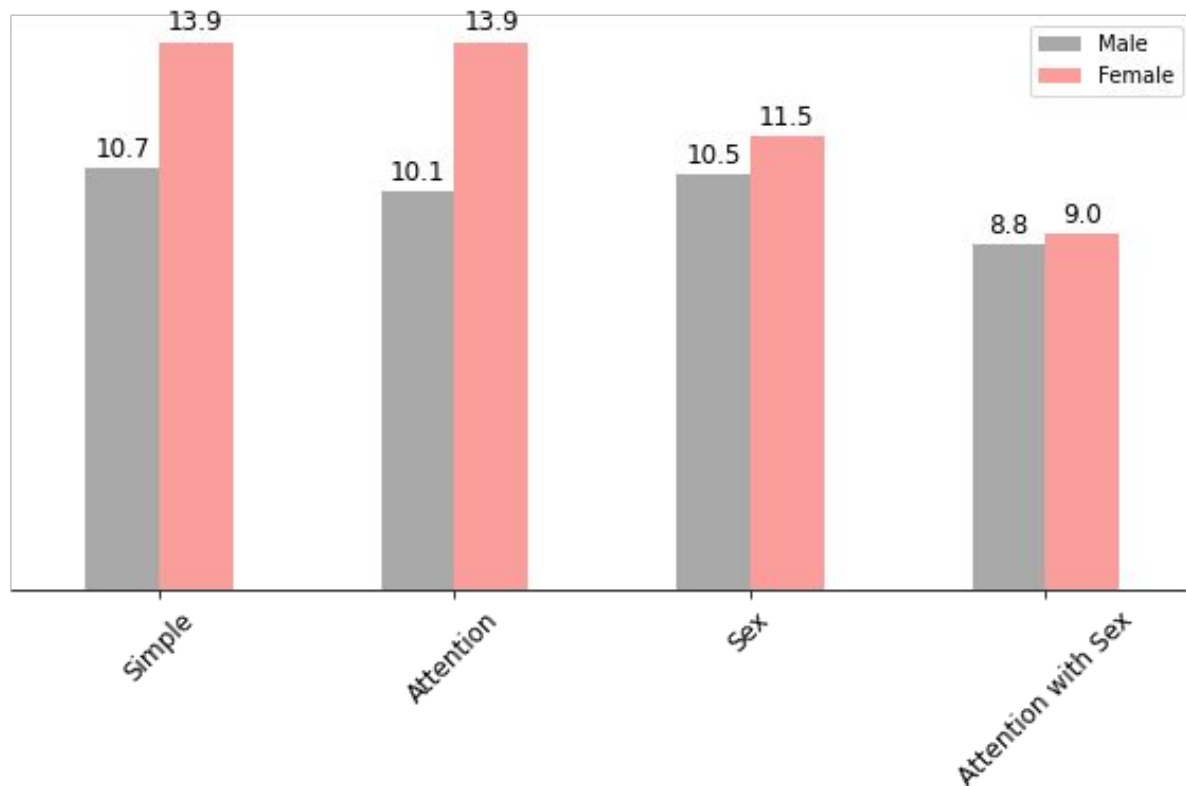
Insight: **Sex**



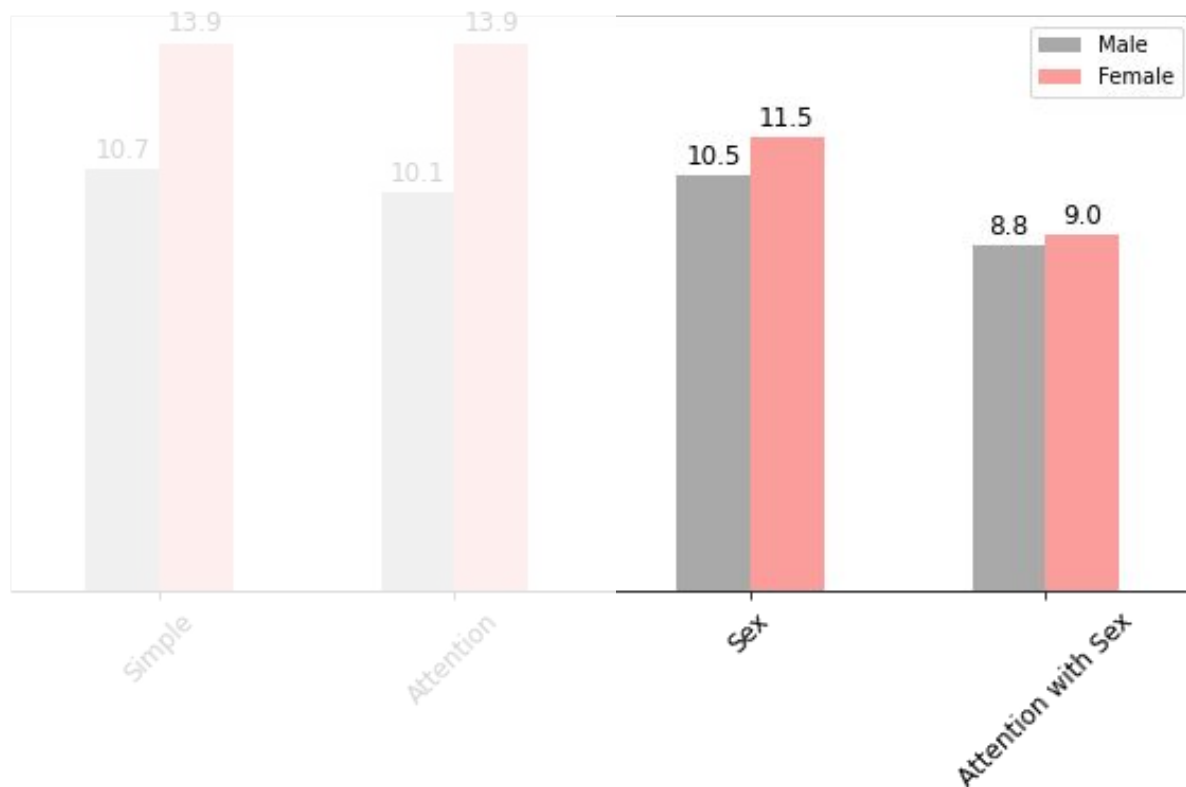
Insight: **Sex**



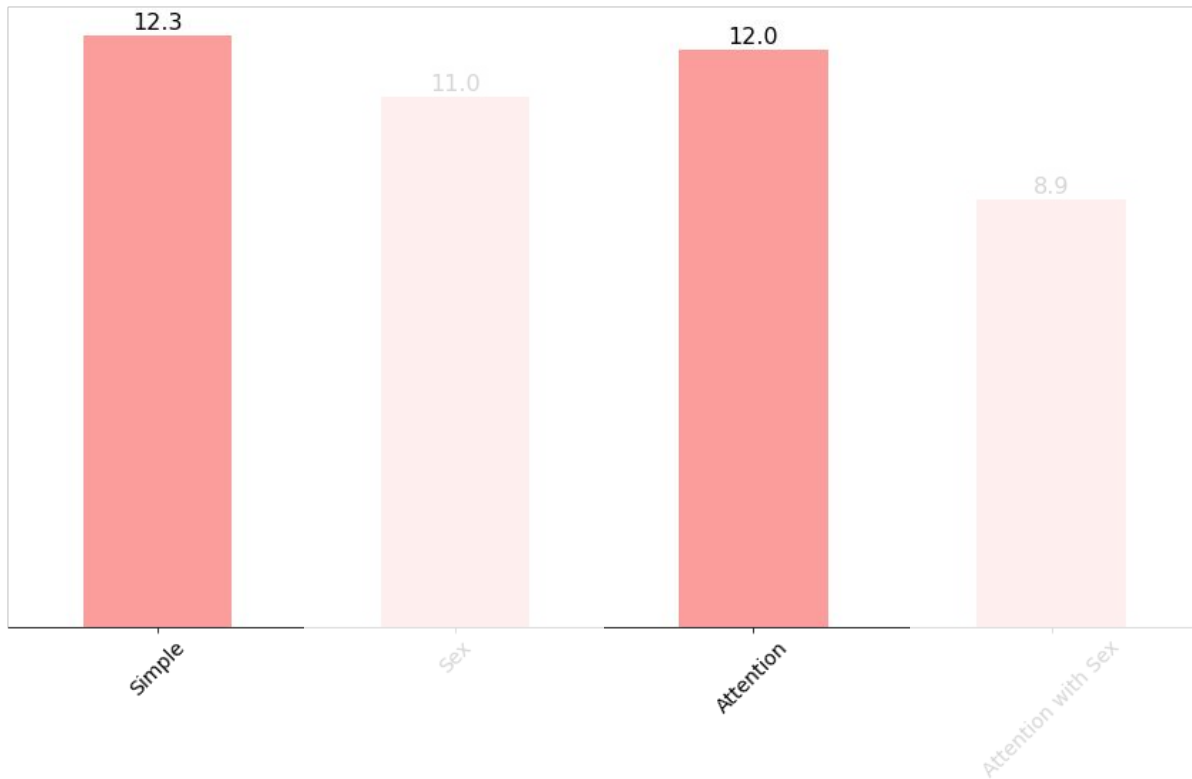
Insight: Sex



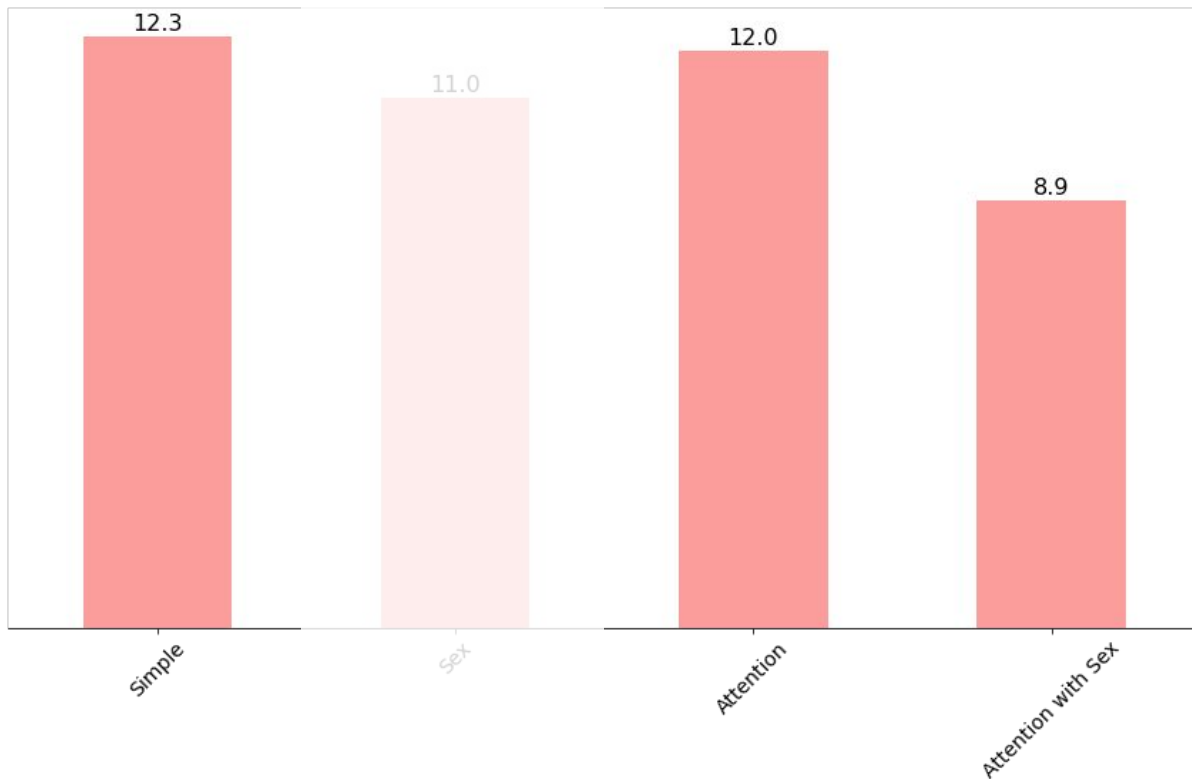
Insight: **Sex**



Insight: Attention

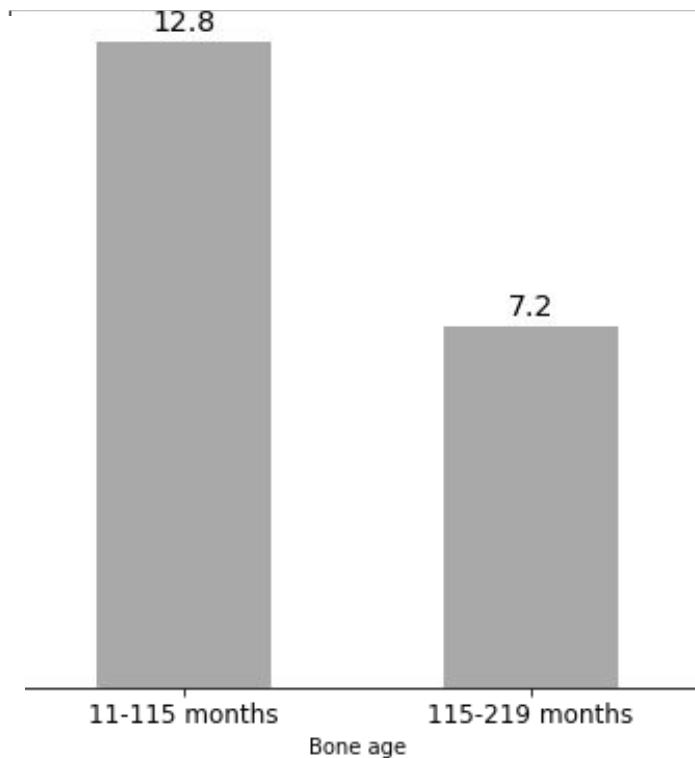


Insight: Attention + Sex



Insight: Age

**Attention-sex model:
MAE (months)**



Takeaways



Consider sex differences, which may be associated with regions of interest

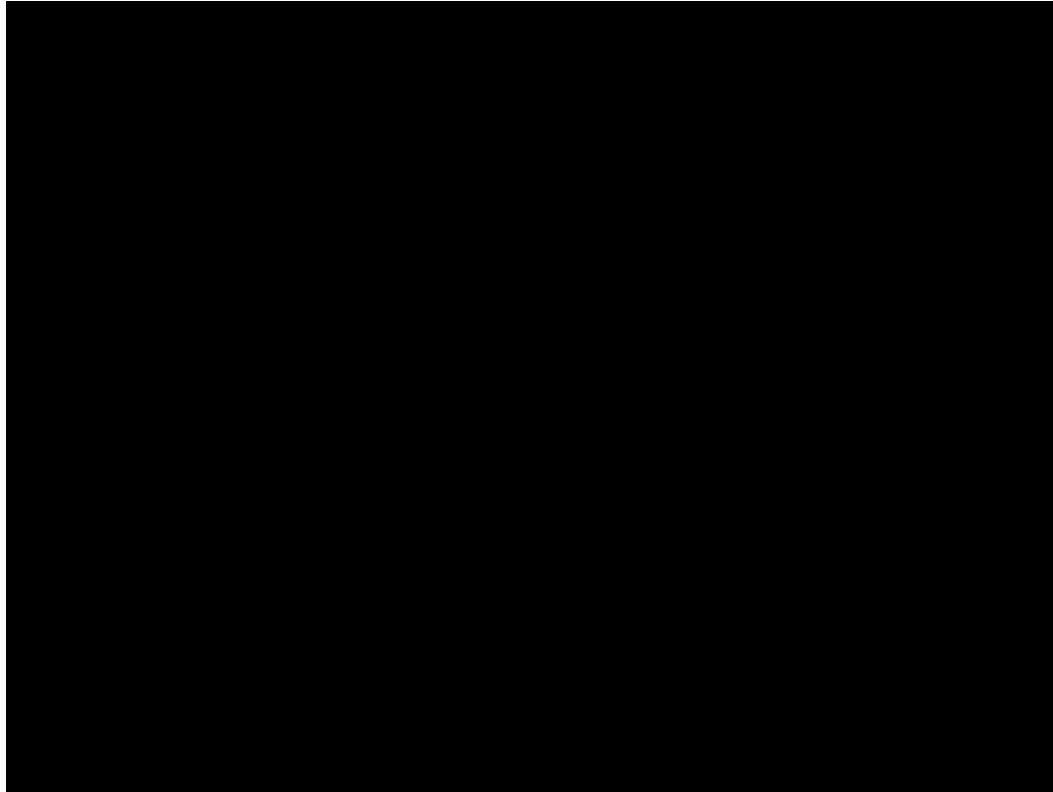


Pre-identifying regions of interest may improve performance

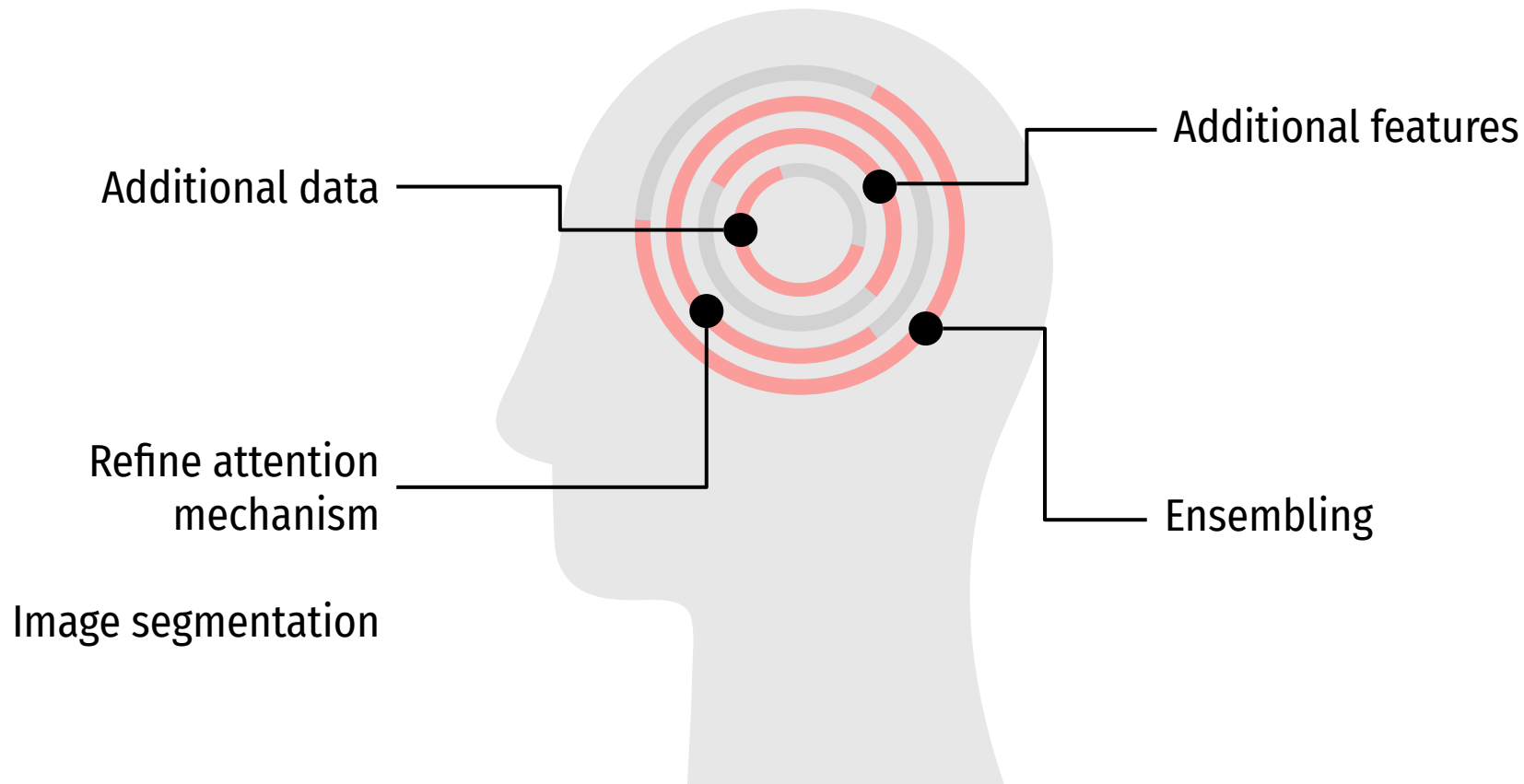


Consider age differences

Application



Future Work



References

Data sources:

- <https://www.rsna.org/education/ai-resources-and-training/ai-image-challenge/RSNA-Pediatric-Bone-Age-Challenge-2017>
- <https://stanfordmedicine.app.box.com/s/4r1zwio6z6lrzk7zw3fro7ql5mnoupcv/folder/42459416739>
- <https://www.kaggle.com/kmader/rsna-bone-age>

Chollet, F. <https://github.com/fchollet/deep-learning-with-python-notebooks/blob/master/5.3-using-a-pretrained-convnet.ipynb>. [Accessed Dec 2020].

Creo AL, Schwenk WF. Bone age: a handy tool for pediatric providers. *Pediatrics*. 2017;140(6):e20171486.

F. Chollet, "Xception: Deep Learning with Depthwise Separable Convolutions," *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Honolulu, HI, 2017, pp. 1800-1807, doi: 10.1109/CVPR.2017.195.

H. Fukui, T. Hirakawa, T. Yamashita and H. Fujiyoshi, "Attention Branch Network: Learning of Attention Mechanism for Visual Explanation," *2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, Long Beach, CA, USA, 2019, pp. 10697-10706, doi: 10.1109/CVPR.2019.01096.

Halabi SS, Prevedello LM, Kalpathy-Cramer J, et al. The RSNA Pediatric Bone Age Machine Learning Challenge. *Radiology* 2018; 290(2):498-503.

Model architecture and code adapted from:

- M. Cicero and A. Bilbily, "Machine Learning and the Future of Radiology: How we won the 2017 RSNA ML Challenge," 16bit.ai, Nov. 23, 2017. [Online]. Available: <https://www.16bit.ai/blog/ml-and-future-of-radiology>. [Accessed Dec 2020].
- Mader, KS. "Attention on Pretrained-VGG16 for Bone Age". <https://www.kaggle.com/kmader/attention-on-pretrained-vgg16-for-bone-age>. [Accessed Dec 2020].
- Ehrhorn, M. "KU BDA 2019 boneage project". <https://www.kaggle.com/ehrhorn2019/ku-bda-2019-boneage-project>. [Accessed Dec 2020].



Thank you!

Questions?

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Predictions

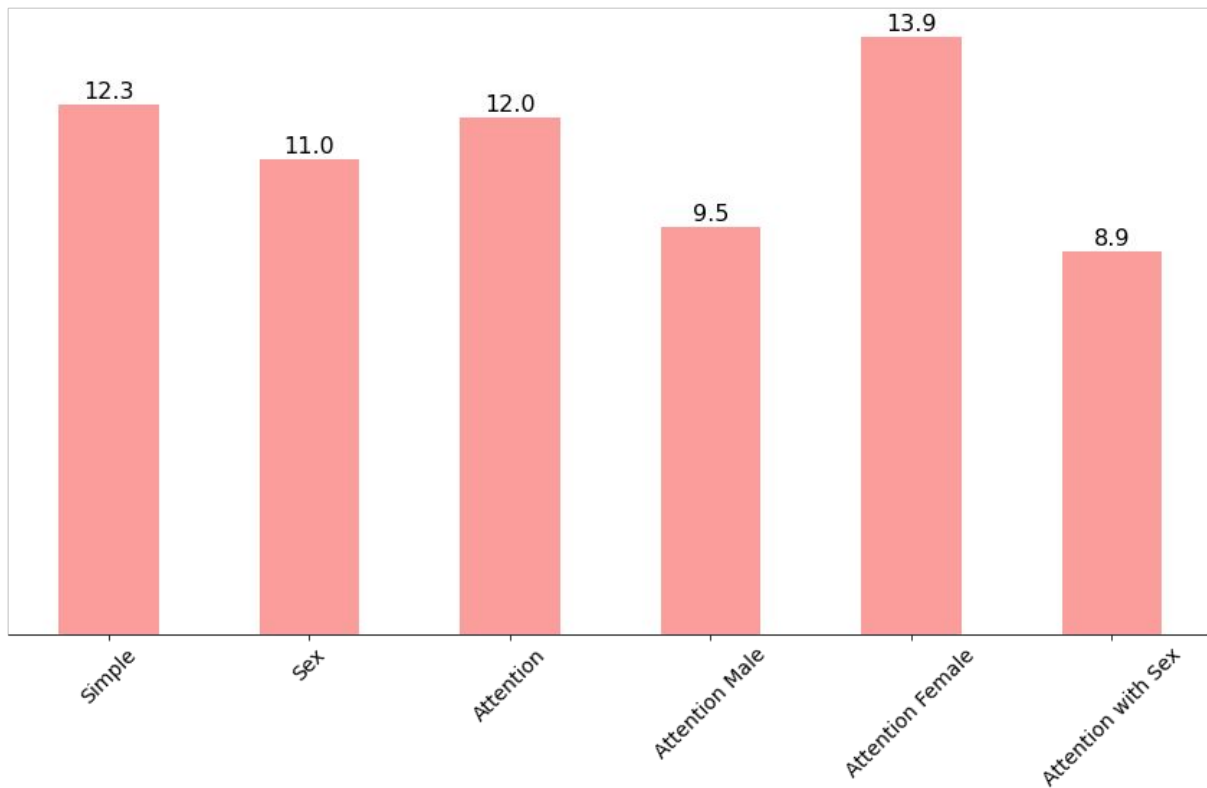
Age: 11.4Y
Predicted Age: 11.4Y



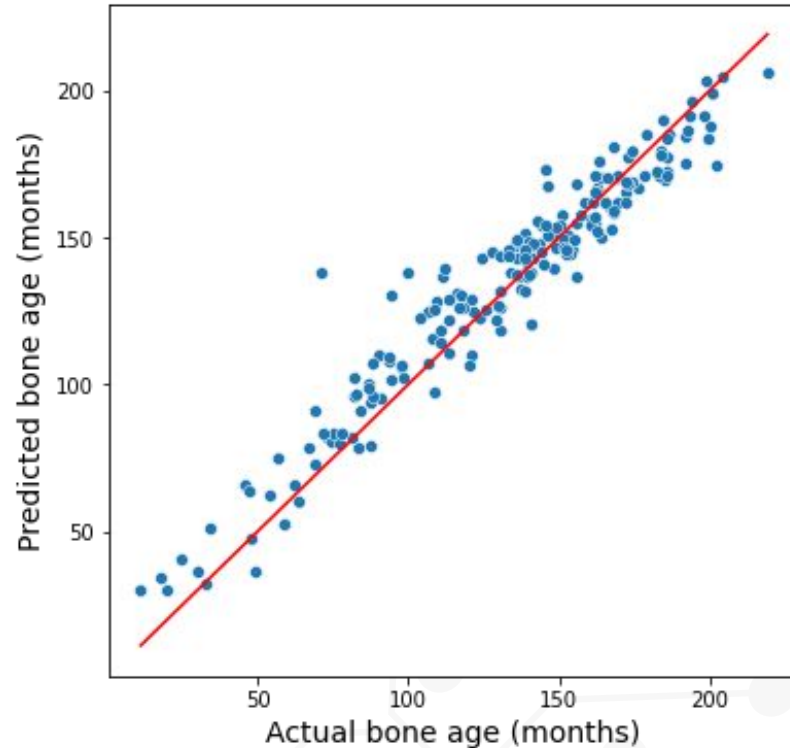
Age: 5.9Y
Predicted Age: 11.5Y



Appendix: Additional Models - MAE (months)



Appendix: Best Model Predictions



Appendix: Best Model Diagnostics

