

## 215 A Appendix: SoftStep Regression algorithm

The SoftStep regression algorithm is built on top of neighborhood component analysis [Goldberger et al. 2004]. Given a similarity measure  $sim$  an embedded sample  $z^*$  and embedded neighbors  $Z_N$  we predict

$$\hat{y} = \text{SoftMax}(sim(z^*, Z_N) + \ln(\text{SoftStepPred}(z^*, Z_N)))$$

216 where  $sim$  is a vector of similarities between  $z^*$  and the members of  $Z_N$  and  $\text{SoftStepPred}$  is the module described in Algorithm 1.

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### Algorithm 1 SoftStep for prediction module

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1: procedure SOFTSTEP( $Z, Z_N, \text{SoftStep\_fn}$ )
  Initialization (run once at module construction):
2:    $\text{params} \leftarrow \text{MLP or Linear layer with sigmoid activation}$ 
3:   Store  $\text{SoftStep\_fn}$ 
  Forward Pass:
4:    $(a_0, b_0, t) \leftarrow \text{params}(Z)$ 
5:    $sim \leftarrow \text{SIM}(Z, Z_N)$  ▷ Matrix of similarities
6:    $sim\_norm \leftarrow \text{NORM}(sim)$  ▷ Normalize to [0, 1]
7:   if  $\text{SoftStep\_fn}$  requires  $a$  then
8:     if  $Z_N == Z$  (training) then
9:        $top\_sim \leftarrow \text{row-wise max of } sim\_norm \text{ excluding diagonal}$ 
10:    else
11:       $top\_sim \leftarrow \text{row-wise max of } sim\_norm$ 
12:    end if
13:     $a \leftarrow \min(a_0, top\_sim) - \epsilon$  ▷  $\epsilon > 0$  small
14:     $b \leftarrow a + b_0 \cdot (1 - a)$ 
15:  else
16:     $a \leftarrow a_0$ 
17:     $b \leftarrow b_0$ 
18:  end if
19:   $shift \leftarrow \text{SoftStep\_fn}(sim\_norm, a, b, t)$ 
20:  return  $sim + \log(shift)$ 
21: end procedure

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## 217 B SoftStep prediction experiments

219 See Table 2 for results.

220 Exact model versions and pretrained weights are specified in the included GitHub repository. We  
 221 ensured that at least two distinct feature extractors were chosen per unstructured modality (text, audio,  
 222 and image) to demonstrate the generalizability of our proposed algorithm. The following is a list of  
 223 datasets and feature extractors used to conduct our experiments:

224 **RSNA Bone Age Prediction** The Radiological Society of North America (RSNA) Pediatric Bone  
 225 Age Machine Learning Challenge collected pediatric hand radiographs labeled with the age of the  
 226 subject in months [Halabi et al. 2019]. We collected 14,036 images from this dataset. Images were  
 227 resized to 224x224 pixels, normalized with mean and standard deviation of 0.5 across the single  
 228 gray-scale channel and input to ResNet-18 pretrained on ImageNet [He et al. 2016], [He and Jiang  
 229 2021].

230 **ADReSSo** The Alzheimer’s Dementia Recognition through Spontaneous Speech only (ADReSSo)  
 231 diagnosis dataset has 237 audio recordings of participants undergoing the Cookie Thief cognitive  
 232 assessment labeled with their score on the Mini Mental State Exam [Luz et al. 2021]. Transcripts of  
 233 these recordings were tokenized and input to DistilBERT-base-uncased [Sanh 2019], [Zolnoori et al.  
 234 2023].

[https://pytorch.org/hub/pytorch\\_vision\\_resnet/](https://pytorch.org/hub/pytorch_vision_resnet/)

[https://huggingface.co/docs/transformers/en/model\\_doc/distilbert](https://huggingface.co/docs/transformers/en/model_doc/distilbert)

Dataset	Linear	SoftStep
RSNA <a href="#">Halabi et al. [2019]</a>	$5.12 \pm 0.608$	$4.13 \pm 0.235$
MedSegBench <a href="#">Kuş and Aydın [2024]</a>	$6.69 \pm 1.29$	$4.02 \pm 0.608$
ADReSSo <a href="#">Luz et al. [2021]</a>	$96.2 \pm 33.3$	$28.0 \pm 4.13$
CoughVid <a href="#">Orlandic et al. [2021]</a>	$39.7 \pm 27.0$	$21.2 \pm 0.195$
NoseMic <a href="#">Butkow et al. [2024]</a>	$7.96 \pm 0.947$	$6.01 \pm 0.472$
Udacity <a href="#">Du et al. [2019]</a>	$0.435 \pm 0.170$	$0.358 \pm 0.104$
Pitchfork <a href="#">Pinter et al. [2020]</a>	$69.6 \pm 167.0$	$10.2 \pm 1.01$
Houses <a href="#">Ahmed and Moustafa [2016]</a>	$303 \pm 81.3$	$13.2 \pm 1.77$
Books (see below)	$8.33 \pm 0.680$	$7.48 \pm 0.588$
Austin (see below)	$2.29 \pm 0.216$	$2.05 \pm 0.231$

Table 2: Average mean squared error (MSE)  $\pm$  standard deviation across ten random splits of each dataset. The best mean results for each dataset are shown in bold. All values are scaled by  $10^3$  for readability. A complete description of each dataset, including preprocessing pipelines and feature extractors, is provided.

**MedSegBench** The MedSegBench BriFiSegMSBench dataset is comprised of single-channel microscopy images and corresponding segmentation masks [Kuş and Aydın \[2024\]](#). We estimated the size of segmentation mask areas using EfficientNet trained on ImageNet. [Rizk et al. \[2014\]](#), [Tan and Le \[2019\]](#).<sup>3</sup>

**CoughVid** The CoughVid dataset provides over 25,000 crowdsourced cough recordings, with 6,250 recordings labeled with participant age in years [Orlandic et al. \[2021\]](#). One second of cough audio was input to HuBERT pretrained on LibriSpeech and mean-pooled across time [Hsu et al. \[2021\]](#), [Feng et al. \[2024\]](#).<sup>4</sup>

**NoseMic** The NoseMic dataset collected 1,297 30-second audio recordings of heart rate-induced sounds in the ear canal using an in-ear microphone under several activities [Butkow et al. \[2024\]](#). Audio clips were denoised,<sup>5</sup> encoded with the Whisper tiny audio encoder [Radford et al. \[2023\]](#), and mean-pooled across time.<sup>6</sup>

**Udacity** The Udacity self-driving car dataset is comprised of dashcam videos labeled with the angle of the car’s steering wheel [Du et al. \[2019\]](#). Videos were downsampled to 4 frames per second for a total of 6,762 images and individual frames were input to EfficientNet trained on ImageNet [Tan and Le \[2019\]](#).<sup>3</sup>

**Pitchfork** 24,649 reviews from the website Pitchfork were collected [Pinter et al. \[2020\]](#), where albums are scored from 0 to 10 in 0.1 increments. 1,500 randomly selected reviews were tokenized and input to BERT base [Warner et al. \[2024\]](#).<sup>7</sup>

**Houses** The Houses dataset collects 535 curbside images of houses as well as their log-scaled list price [Ahmed and Moustafa \[2016\]](#). Images were resized to 256x256 pixels, center cropped to 224x224, ImageNet normalized, and input to ResNet-34 [He et al. \[2016\]](#).<sup>8</sup>

**Books** The MachineHack Book Price Prediction dataset collated 6237 synopses of books labeled with their log-normalized price.<sup>8</sup> Synopses were tokenized and input to DistilBERT-base-uncased.<sup>2</sup>

**Austin** The Kaggle Austin Housing Prices dataset collects over 15000 descriptions of homes labeled with their log-scaled list price.<sup>9</sup> Descriptions were tokenized and input to DistilBERT-base-uncased.<sup>2</sup>

<sup>3</sup><https://docs.pytorch.org/vision/main/models/efficientnet.html>

<sup>4</sup><https://huggingface.co/facebook/hubert-base-ls960>

<sup>5</sup><https://pypi.org/project/noisereduce>

<sup>6</sup><https://huggingface.co/openai/whisper-tiny>

<sup>7</sup><https://huggingface.co/google-bert/bert-base-uncased>

<sup>8</sup>[https://machinehack.com/hackathons/predict\\_the\\_price\\_of\\_books/overview](https://machinehack.com/hackathons/predict_the_price_of_books/overview)

<sup>9</sup><https://www.kaggle.com/datasets/ericpierce/austinhousingprices>