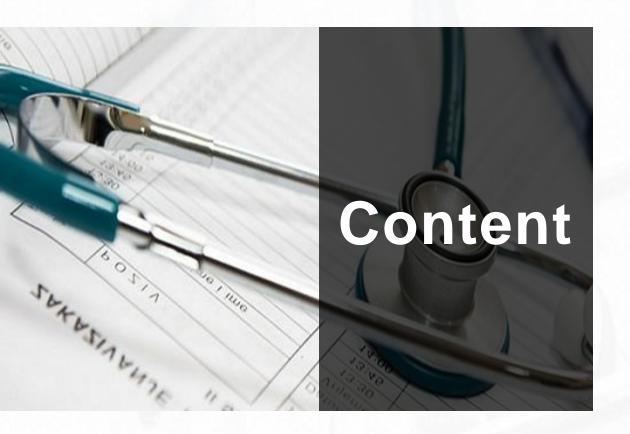


# Design an age estimation algorithm based on multi-task Neural Process

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### Introduction

What's this project want to solve

### Model

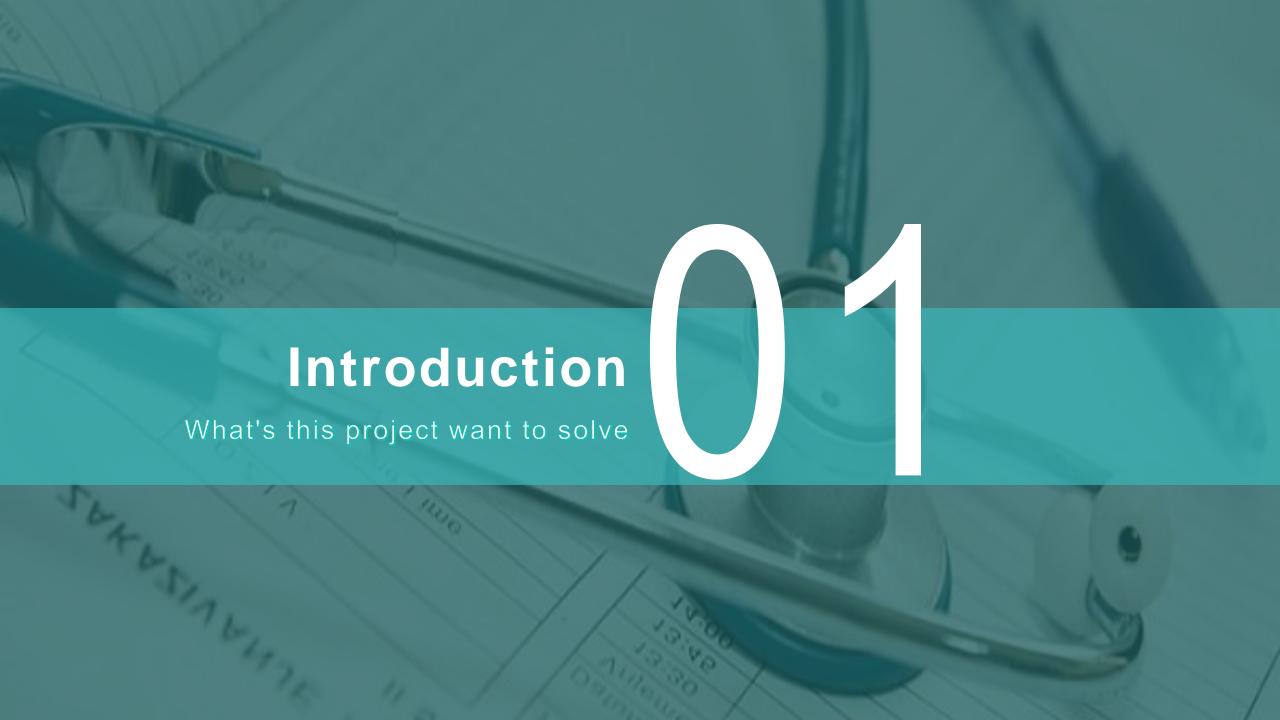
Outlook of the Neural Process

### Method

What we have done

### Plan

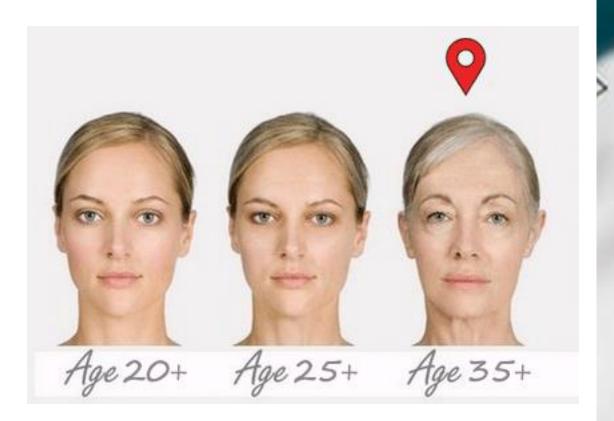
Our Future Work

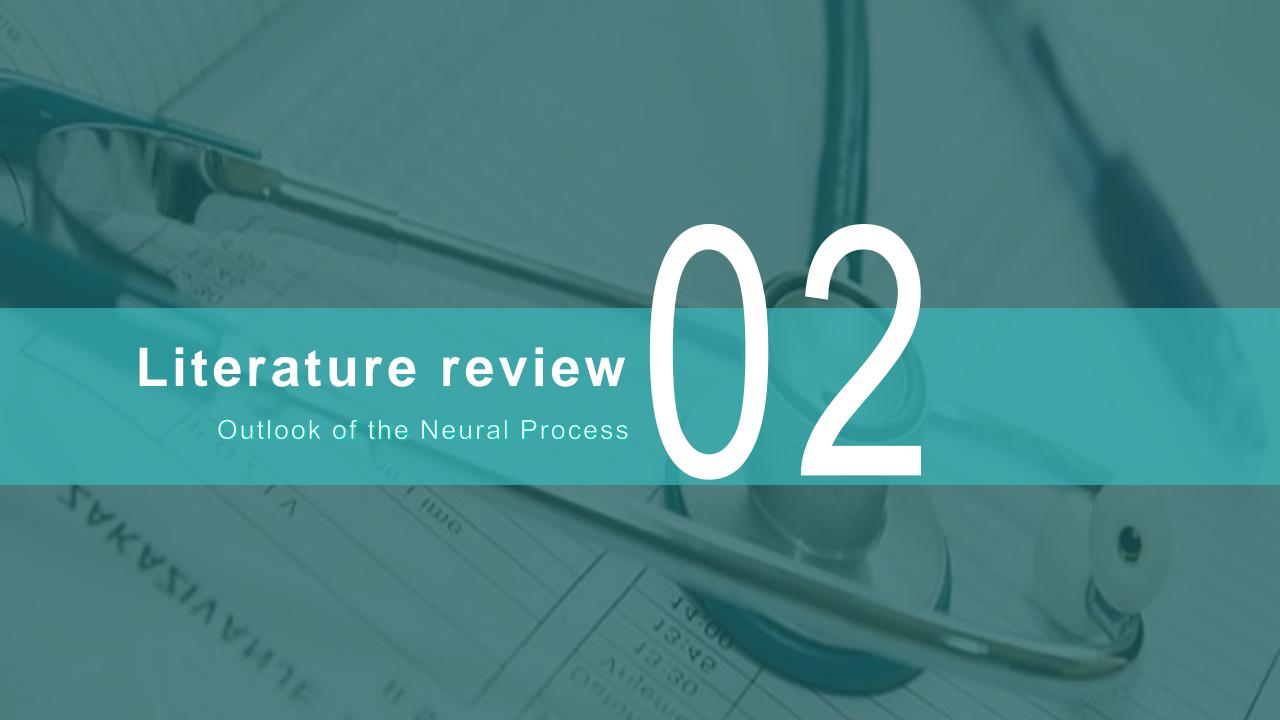


### **Definition**

### What is the meaning of age estimation?

- -According to a single image, implement an end-to-end system
- -to estimate the approximate age of this person.





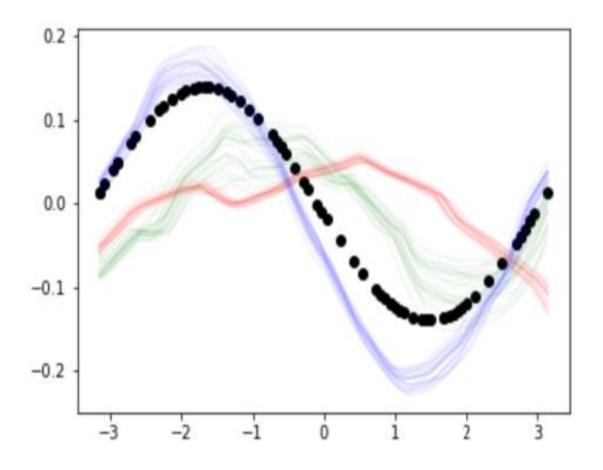


## Neural Processes

 Neural Processes (NPs) are a neural network (NN) based probabilistic model which can represent a distribution over functions:

### Test scenario: NP One-Dimension Regression

https://github.com/LuckyOne09/neural-processes/blob/master/experiments/example-1d.ipynb



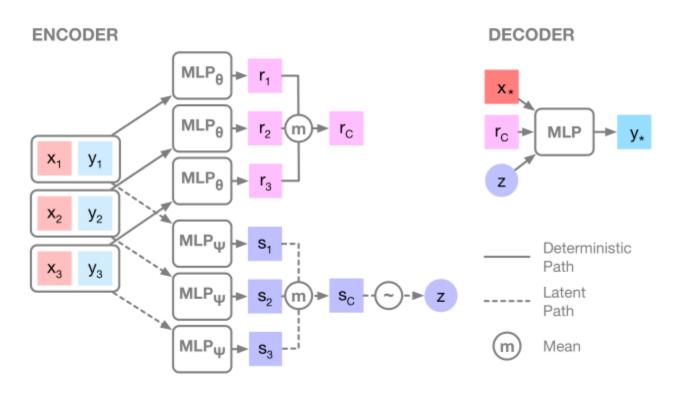
Neural Process for a simple class of 1D functions. The functions are defined by f(x) = a \* sin(x - b) where a and b and randomly sampled.

Red line: context points: 2 Green line: context points: 20 Blue line: context points: 50

Black line: context points

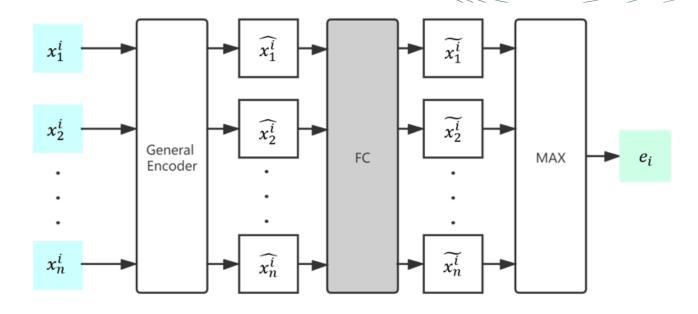


#### **NEURAL PROCESS**









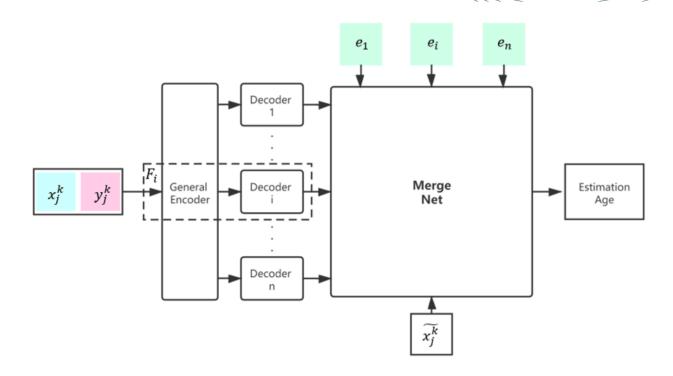
Shared Encoder:  $\widehat{x_j^i} = E(x_i^j)$ 

FC: A fully connected layer we defined  $\tilde{x_j^i} = \sigma(W\hat{x_j^i})$ 

MAX: To get subject embedding. The max operator is conducted elementwisely

$$e_i = \max_j (\widetilde{x_j^i})$$

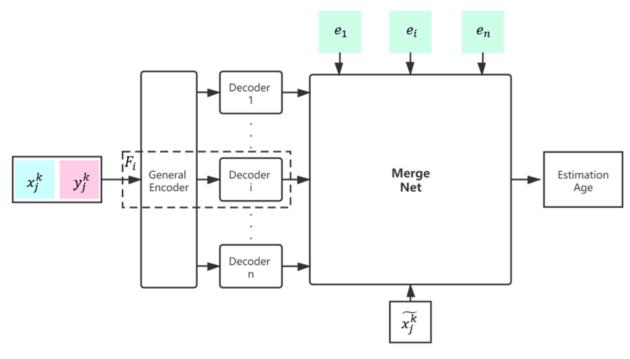




We define the similarity between pth subject and  $\widetilde{x_j^k}$  as  $s_{p,k,j}$ 

$$s_{p,k,j} = \frac{\exp(e_p^T \widetilde{x_j^k})}{\sum_{q \neq k} \exp(e_p^T \widetilde{x_j^k})}$$





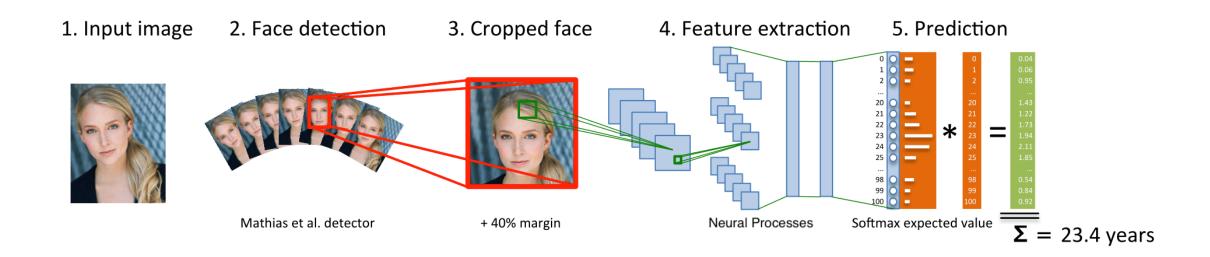
The Estimation Age:  $\sum_{\substack{p=1 \ p \neq k}}^n s_{p,k,j} F_p(x_j^k)$ 

Actually we are here to train the FC we defined The objective function to learn parameters:

$$\min_{W} \sum_{k=1}^{n} \sum_{j=1}^{n_k} \left( y_j^k - \sum_{\substack{p=1\\p \neq k}}^{n} s_{p,k,j} F_p(\widehat{x_j^k}) \right)$$









# processes: Face Detection



# Brightness adjustment and contrast adjustment adjustment

Brightness adjustment

were the color and brightness of the image. To encode invariance to varying color contrast between images, we introduced brightness adjustment with a random scale factor  $\alpha$  per image, sampled from a uniform distribution over [-0.3, 0.3], through equation 1,

$$y = (x - \text{mean}) \times (1 + \alpha) \tag{1}$$

#### Contrast adjustment

and contrast adjustment with a random scale factor  $\beta$  per image, sampled from a uniform distribution over [-0.2, 0.2], using equation 2.

$$y = (x - \text{mean}) \times (\beta) \tag{2}$$

# Pre - processes: Face Cropping

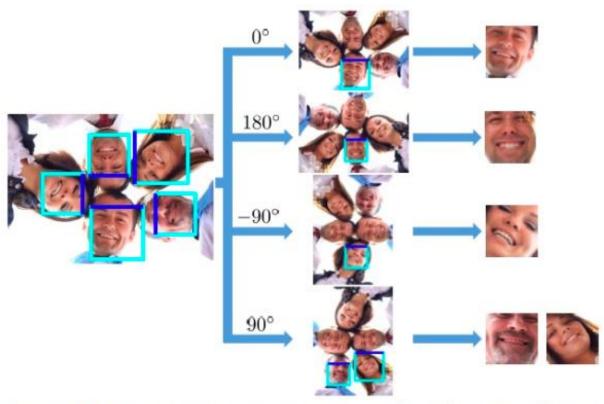
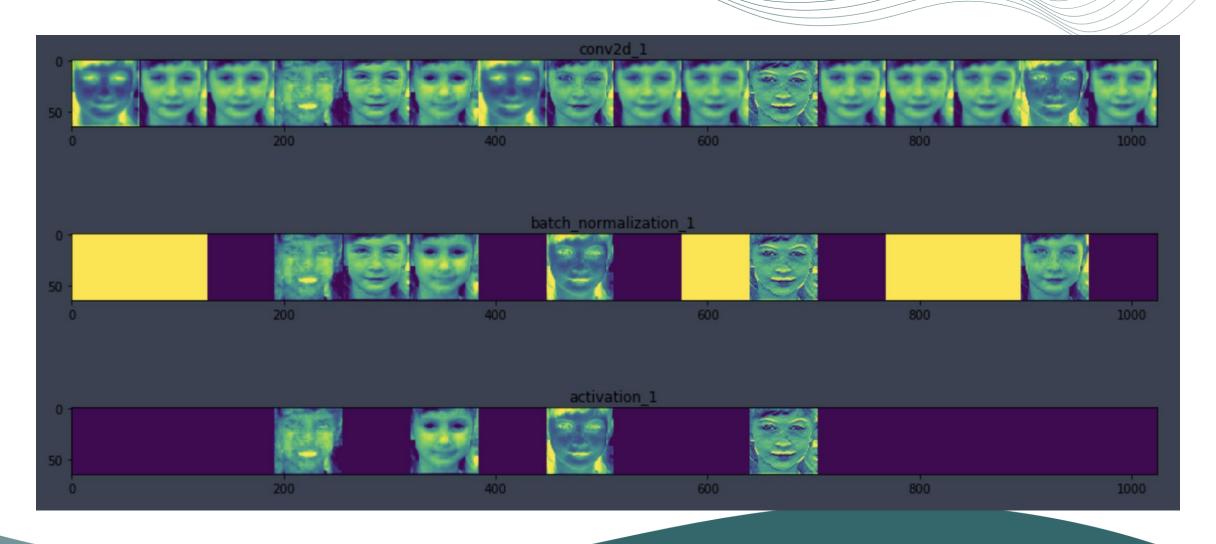
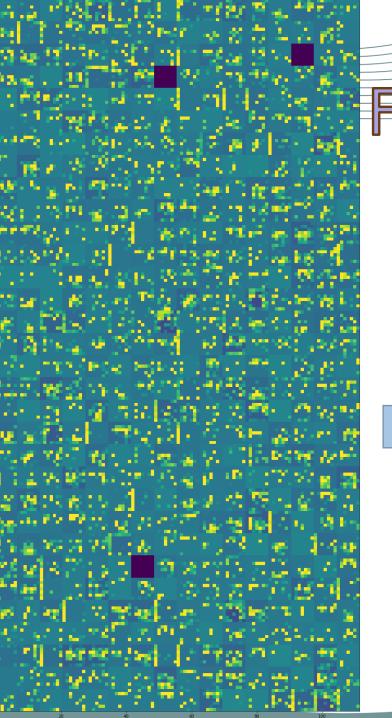


Figure 5. Rotate the original image by  $-90^{\circ}$ ,  $90^{\circ}$ , and  $180^{\circ}$  to get



# Layer Visualization





# Feature

**Abstract** 

# Extractio n

**Abstract** 

# Model

activation_879 (Activation)	(None,	7, 7	, 2048)	0	add_287[0][0]
res5c_branch2a (Conv2D)	(None,	7, 7	, 512)	1049088	activation_879[0][0]
bn5c_branch2a (BatchNormalizati	(None,	7, 7	, 512)	2048	res5c_branch2a[0][0]
activation_880 (Activation)	(None,	7, 7	, 512)	0	bn5c_branch2a[0][0]
res5c_branch2b (Conv2D)	(None,	7, 7	, 512)	2359808	activation_880[0][0]
bn5c_branch2b (BatchNormalizati	(None,	7, 7	, 512)	2048	res5c_branch2b[0][0]
activation_881 (Activation)	(None,	7, 7	, 512)	0	bn5c_branch2b[0][0]
res5c_branch2c (Conv2D)	(None,	7, 7	, 2048)	1050624	activation_881[0][0]
bn5c_branch2c (BatchNormalizati	(None,	7, 7	, 2048)	8192	res5c_branch2c[0][0]
add_288 (Add)	(None,	7, 7	, 2048)	0	<pre>bn5c_branch2c[0][0] activation_879[0][0]</pre>
activation_882 (Activation)	(None,	7, 7	, 2048)	0	add_288[0][0]
global_average_pooling2d_18 (Gl ====================================	(None,	2048	)	0	activation_882[0][0]

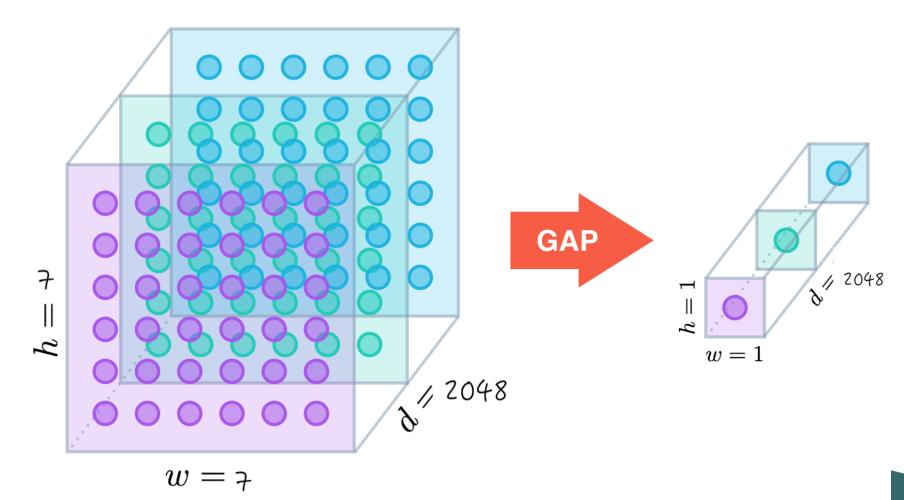
Total params: 23,587,712

Trainable params: 23,534,592
Non-trainable params: 53,120



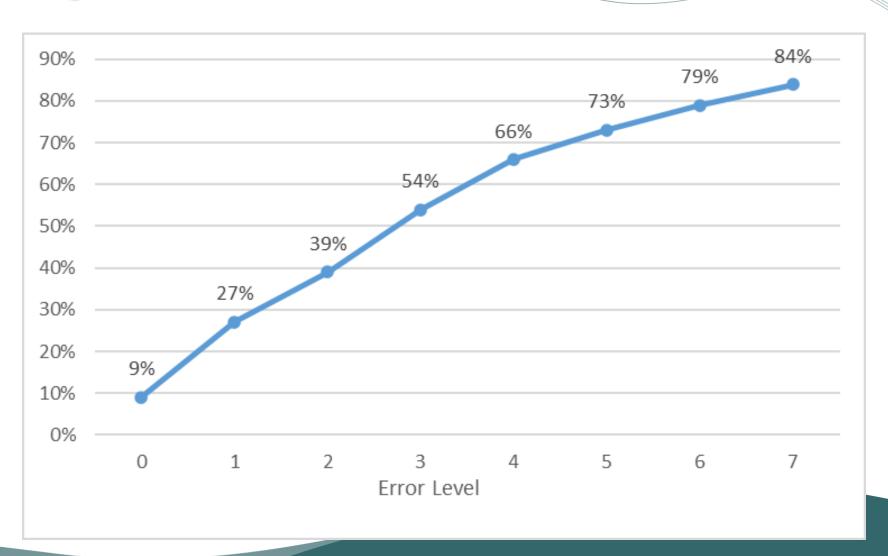
# Global Average Pooling

activation\_49 (Activation) (None, 7, 7, 2048) 0 global\_average\_pooling2d\_1 (None, 2048) 0





### Single Task Estimation



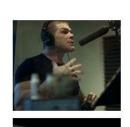
Input image





















Aligned face Apparent age Predicted age



57.75

27.50

17 16.15

40 39.43

50 49.15

30 32.06

79

12 htt 78.99 og. csdn. net 12.781196

Input image

Predicted age







62

43.23











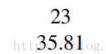
















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