Deep Learning in Healthcare

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(dmytro@ut.ee)

Computational biology - deep learning

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[*]These authors contributed equally to this work
[@]To whom correspondence should be addressed: leopold.parts@sanger.ac.uk (Leopold Parts)

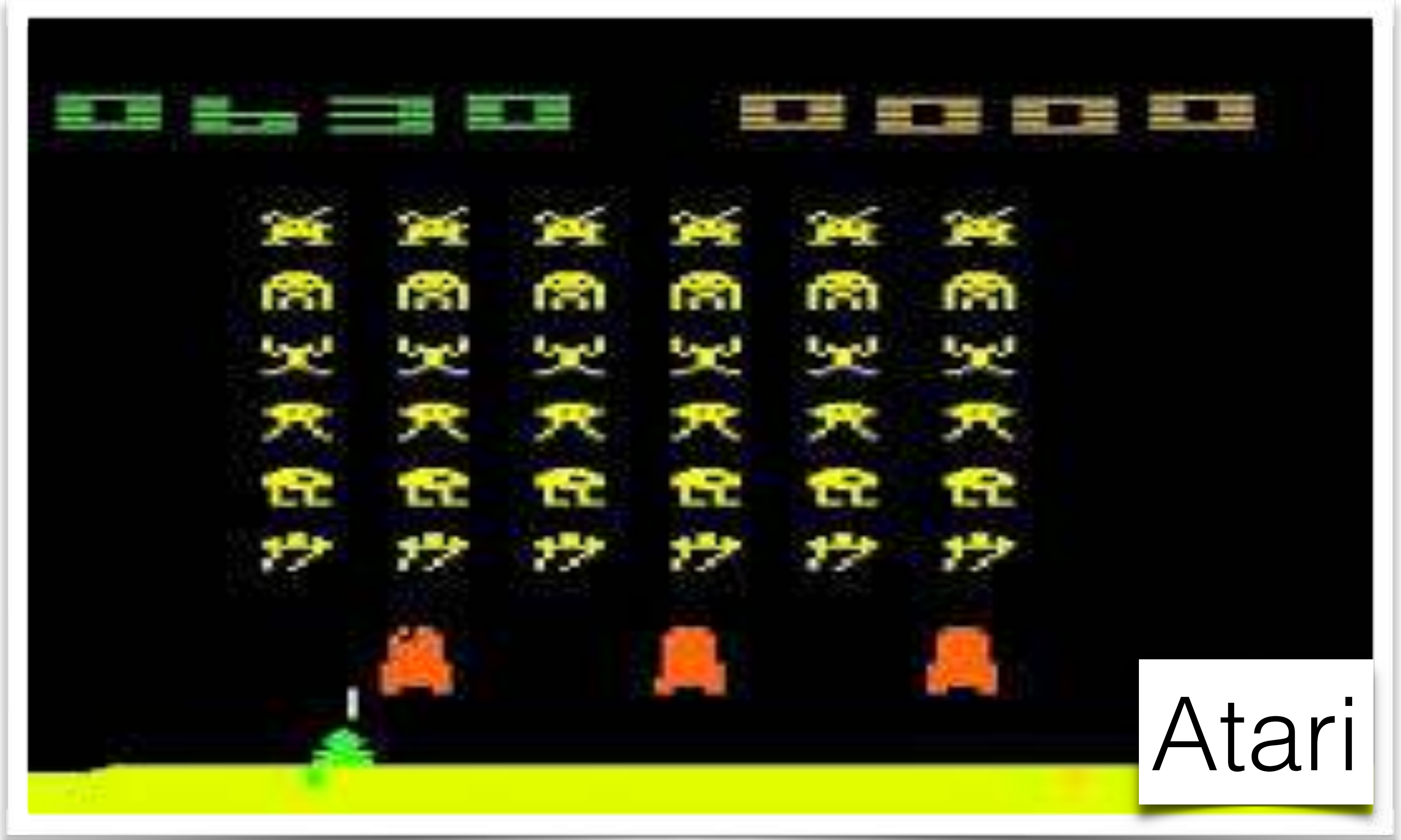
TESLA

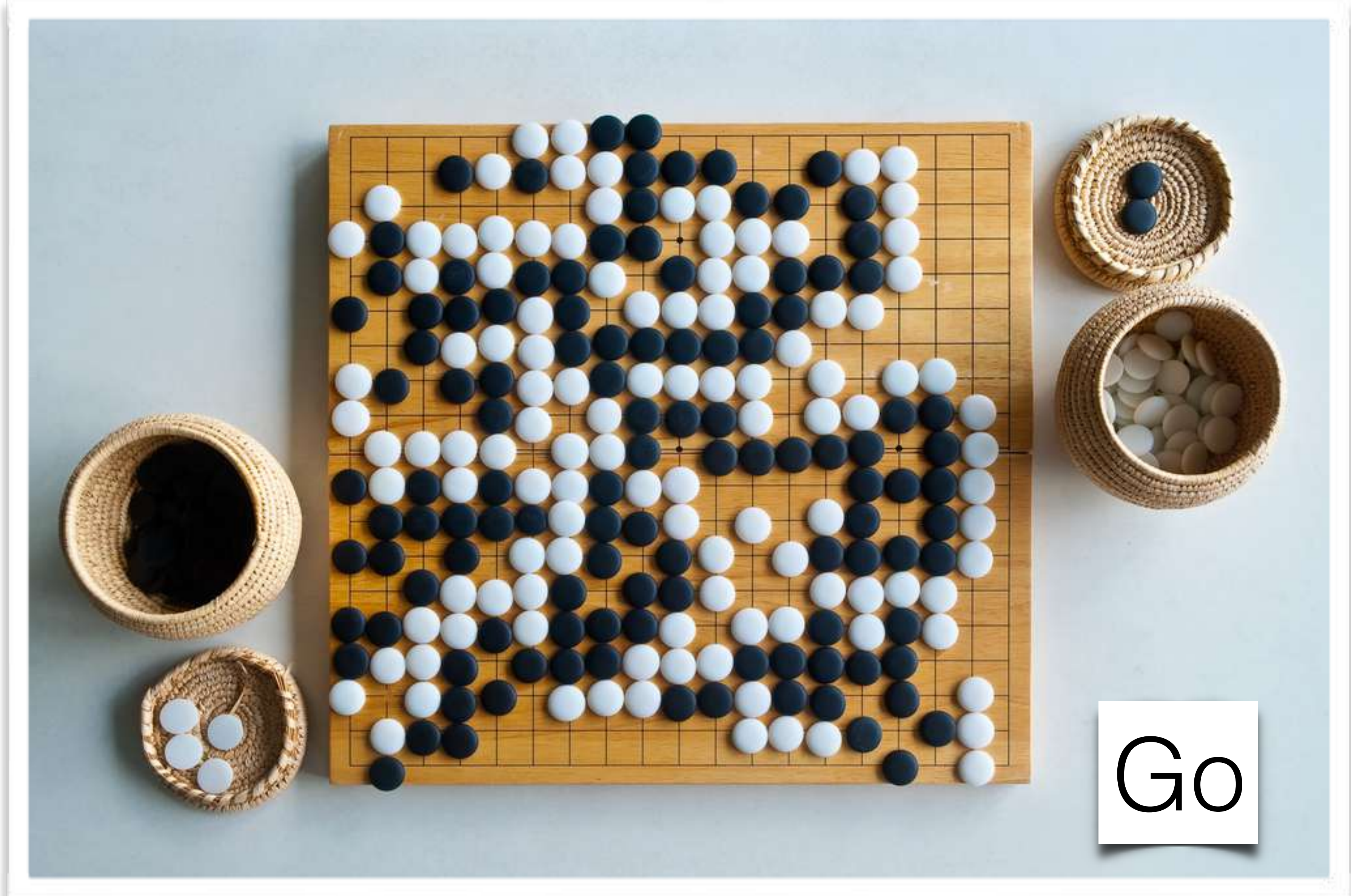
http://thelibertarianrepublic.com/wp-content/uploads/2016/01/self-driving-car1.jpg

http://static.dnaindia.com/sites/default/files/styles/half/public/2016/03/09/435253-skype-translator.jpg?itok=1kAl-u1D

Face ID

Face ID


Atari


Go


Starcraft


Dota 2

How about medical field?

Medicine is complex

Medicine is **really** complex

Human
Metabolism
Propanoate
metabolism
Alanine and
Aspartate
metabolism
Threonine
met.
Methionine
and
cysteine
metabolism
C5-branched dibasic acid
Glycolysis and gluconeogenesis
Citric acid cycle
Oxidative
phosphorylation
Urea
cycle
yruvate met.

ReconMap 2.0


Human Metabolism
Alanine and Aspartate metabolism
Propanoate metabolism
Threonine met.
Methionine and cysteine metabolism
C5-branched dibasic acid
Glycolysis and gluconeogenesis
Citric acid cycle
Oxidative phosphorylatio
Urea cycle
yruvate met.


Human Metabolism
Citric acid cycle
Oxidative phosphorylation
Urea cycle
Pyruvate met.
Tyrosine and phenylalanine metabolism
Chondroitin synthesis and chondroitin sulfate degradation
Heparan sulfate degradation
Pentose phosphate pathway
Starch and sucrose met.
Fructose and mannose met.
Lysine met.
Steroid metabolism
Cholesterol metabolism
Glycine, serine and alanine metabolism
Seleno-aminoacid metabolism
Pyrimidine synthesis and catabolism
O-glycan synthesis
Keratan sulfate synthesis and degradation
Folate metabolism
Fatty acid oxidation
Sphingolipid met.
Blood group synthesis
Vitamin A metabolism
Limonene and pinene degradation
Cytochrome metabolism
UNIVERSITY OF ICELAND
CENTER FOR SYSTEMS BIOLOGY
2012

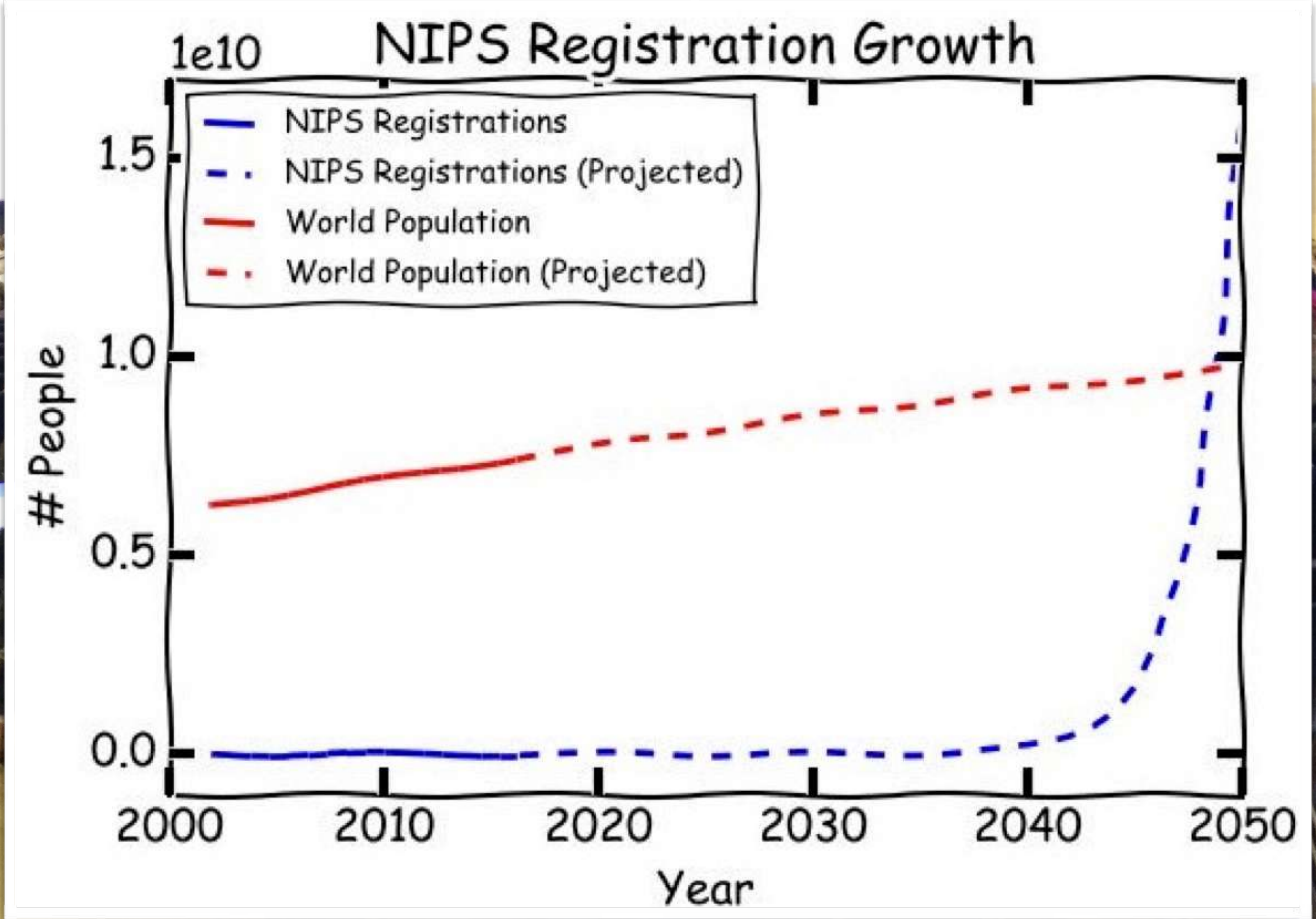
Medicine is massive


Interest over time
100
75
50
25
Super rapid growth
Deep Learning
Note
Jan 1, 2004
Feb 1, 2008
Mar 1, 2012
Apr 1, 2016


100
75
50
25
Fever
Deep Learning
Super rapid growth
Note
Jan 1, 2004
Sep 1, 2008
May 1, 2013

6000 participants at
NIPS 2016 in Barcelona

6000 participants at
NIPS 2016 in Barcelona




8300
RSNA
Your luncheon meeting destination
PHILIPS
Patient IMR
Intellispace Portal
LANDAU
SYNAPSE

54 037 participants at RSNA 2016

Medicine is weird

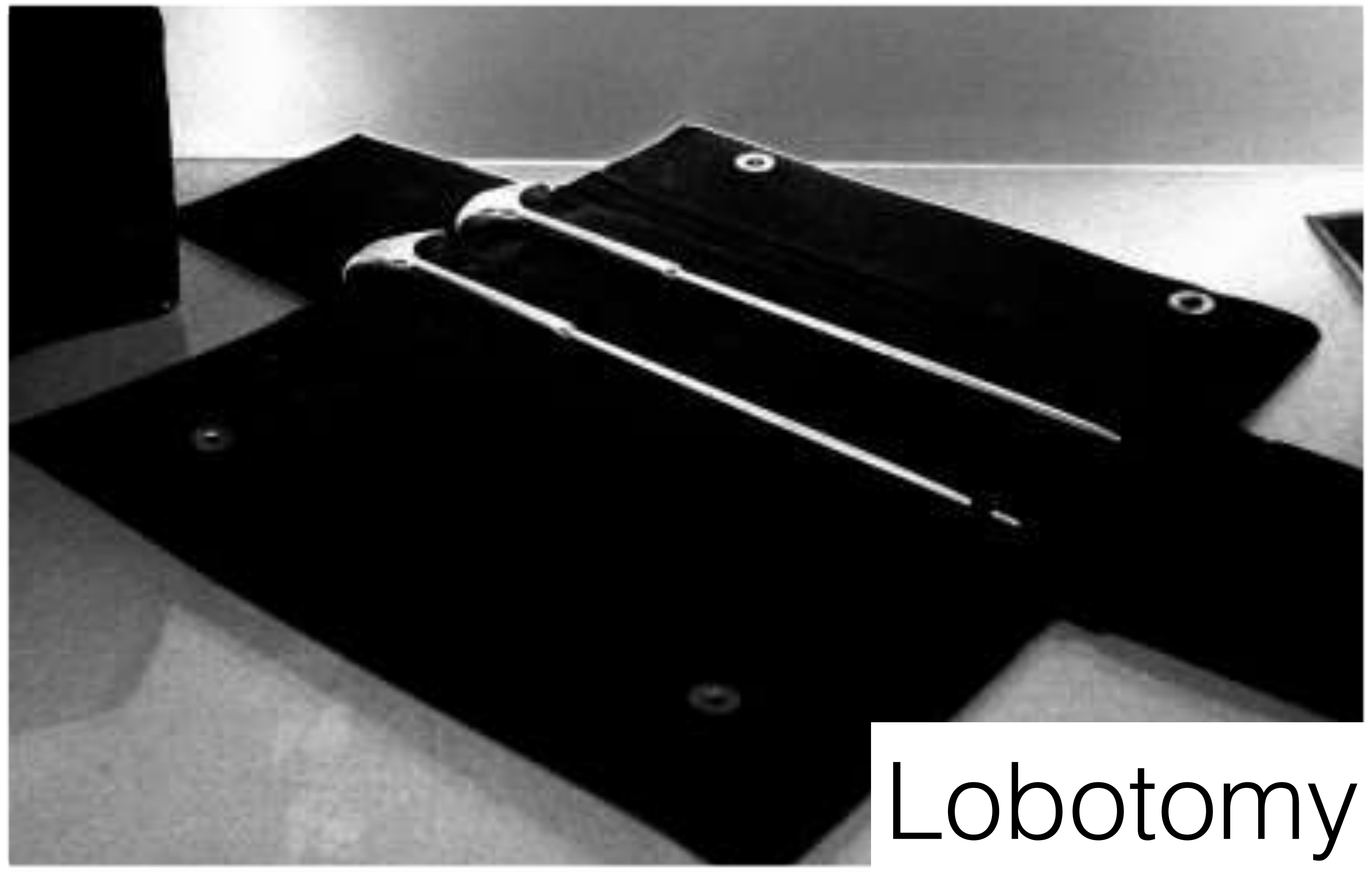

Bloodletting

Bloodletting

Soothing

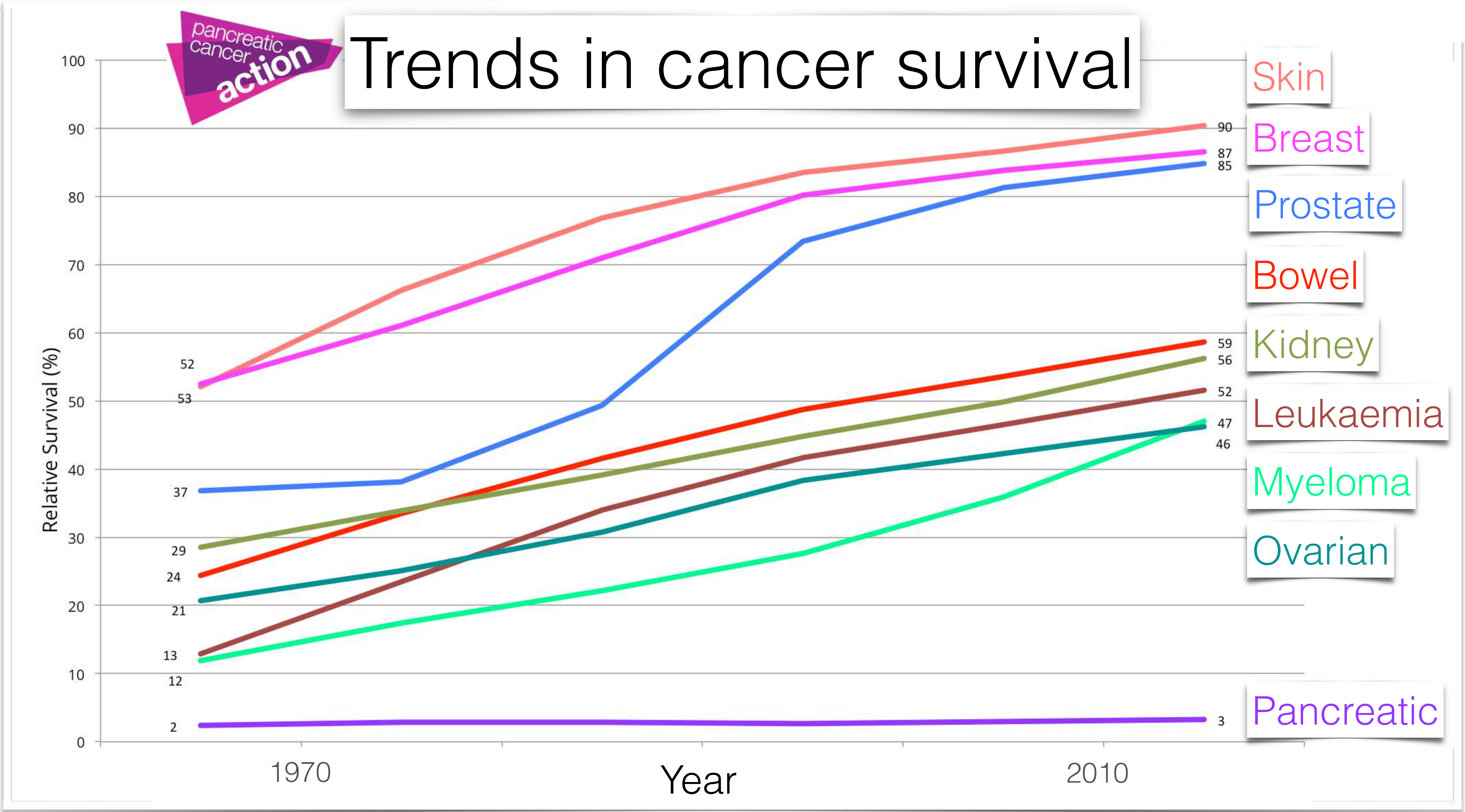
Bloodletting

Soothing



Lobotomy

Nevertheless…



https://pancreaticcanceraction.org/wp-content/uploads/2012/10/Trends-in-cancer-survival-by-tumour-site-1971_2011.png

kaggle Merck Molecular Activity Challenge 2012





In the money · Gold · Silver · Bronze

#	△pub	Team Name	Kernel	Team Members	Score	Entries
1	—	gggg			0.49409	20
2	—	DataRobot			0.48811	37
3	▲2	.			0.48209	88
4	▼1	Gangnam Style			0.48158	43
5	▼1	Luxtorpeda			0.48154	35


AI
GUEST
Patients are about to see a new doctor: arti
intelligence
ALSTON GHAFOURIFAR, ENTEFY
@ENTEFY
JANUARY 31,
Artificial Intelligence could put
lawyers and doctors OUT of a job
t professionals –
Artificial Intelligence
IBM's Watson AI Recommends Same Treatment as Doctors in 99% of Cancer Cases
David Ramos/Getty Images
Blog
Grand Challenges
Will Robots Take Over Our
Experts
Digital Diagnosis: Intelligent Machines Do a Better Job Than Humans
By Anjali Jaiprakash , Jonathan Roberts and Ross Crawford - Jan 18, 2016
8,543
nputer Program Beats Doctors at
tinguishing Brain Tumors from
liation Changes
SCIENCE NEWS × SEPTEMBER 16, 2016
Robots will destroy our jobs - and we're not ready for it
Two-thirds of Americans believe robots will soon perform most of the work done by humans but 80% also believe their jobs will be unaffected. Time to think again

Diabetic Retinopathy

Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs

Skin Cancer

Dermatologist-level classification of skin cancer with deep neural networks

Diabetic Retinopathy

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Diabetic Retinopathy

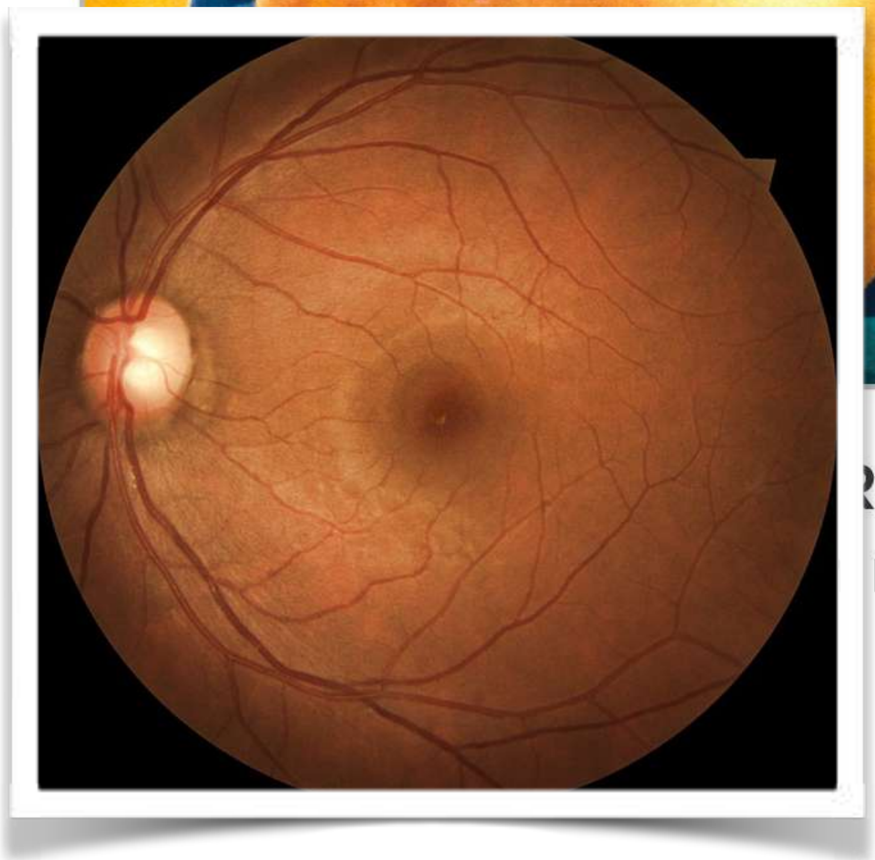
NORMAL VISION
Vision remains intact

Diabetic Retinopathy

NORMAL VISION
Vision remains intact

DIABETIC RETINOPATHY
Vision is obstructed by macular edema

Diabetic Retinopathy



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remains intact

DIABETIC RETINOPATHY
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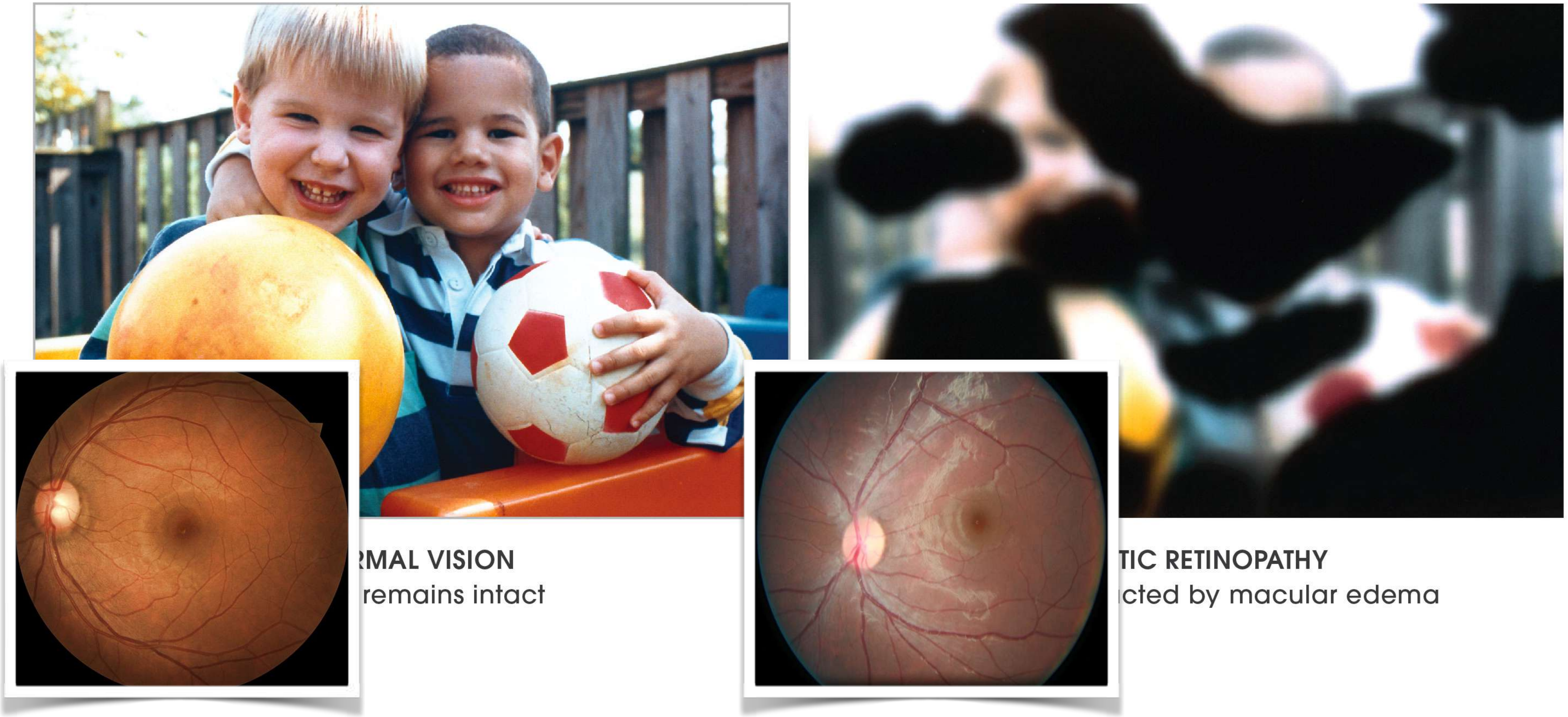
Diabetic Retinopathy




Diagnostics done manually
9 - 12 minutes per patient
Normal retina
Retinopathy
Macula
Optic disk
Hemorrhage
Aneurysms


128 175 images for training


128 175 images for training
54 US licensed ophthalmologists

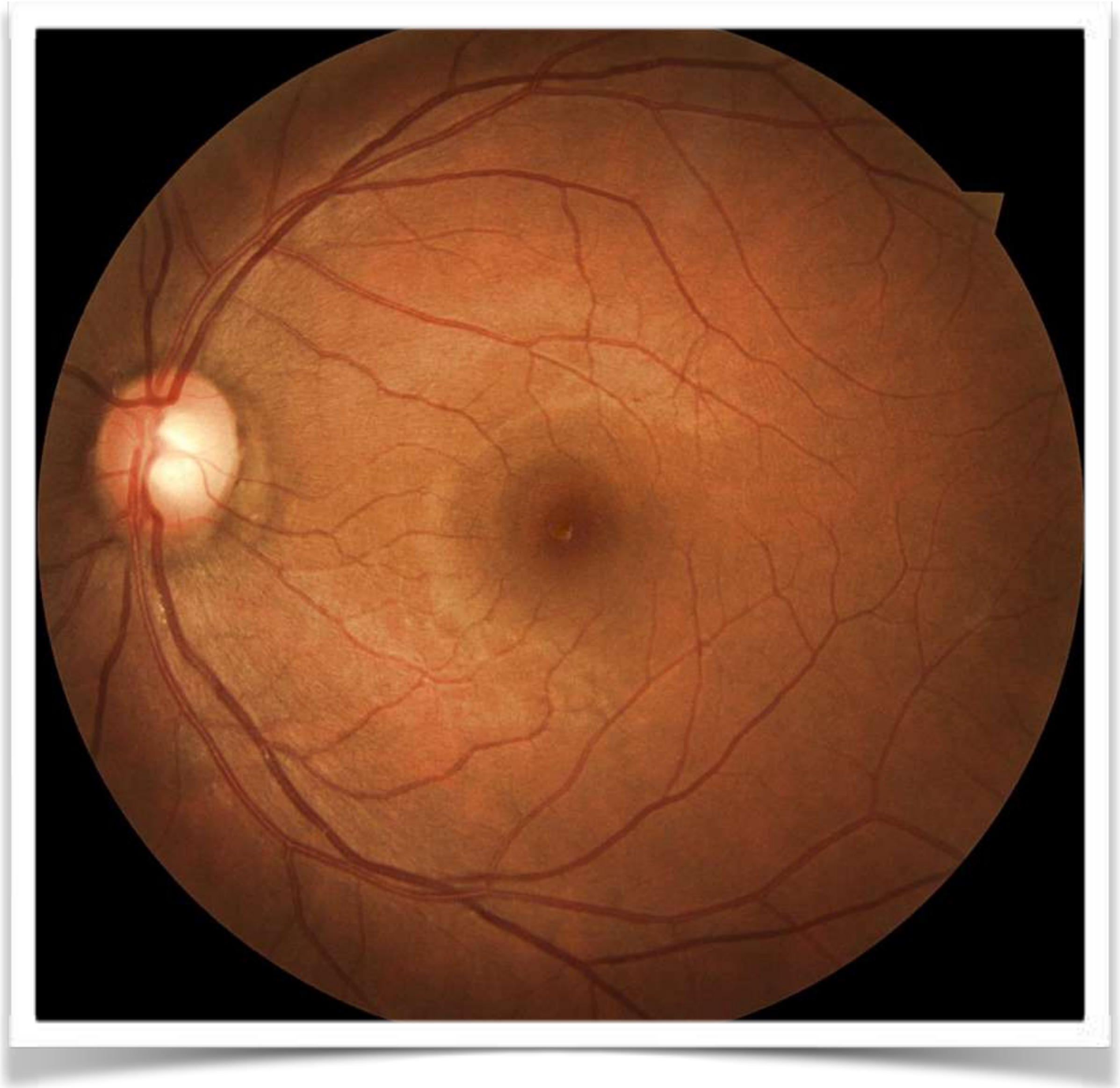
128 175 images for training

54 US licensed ophthalmologists

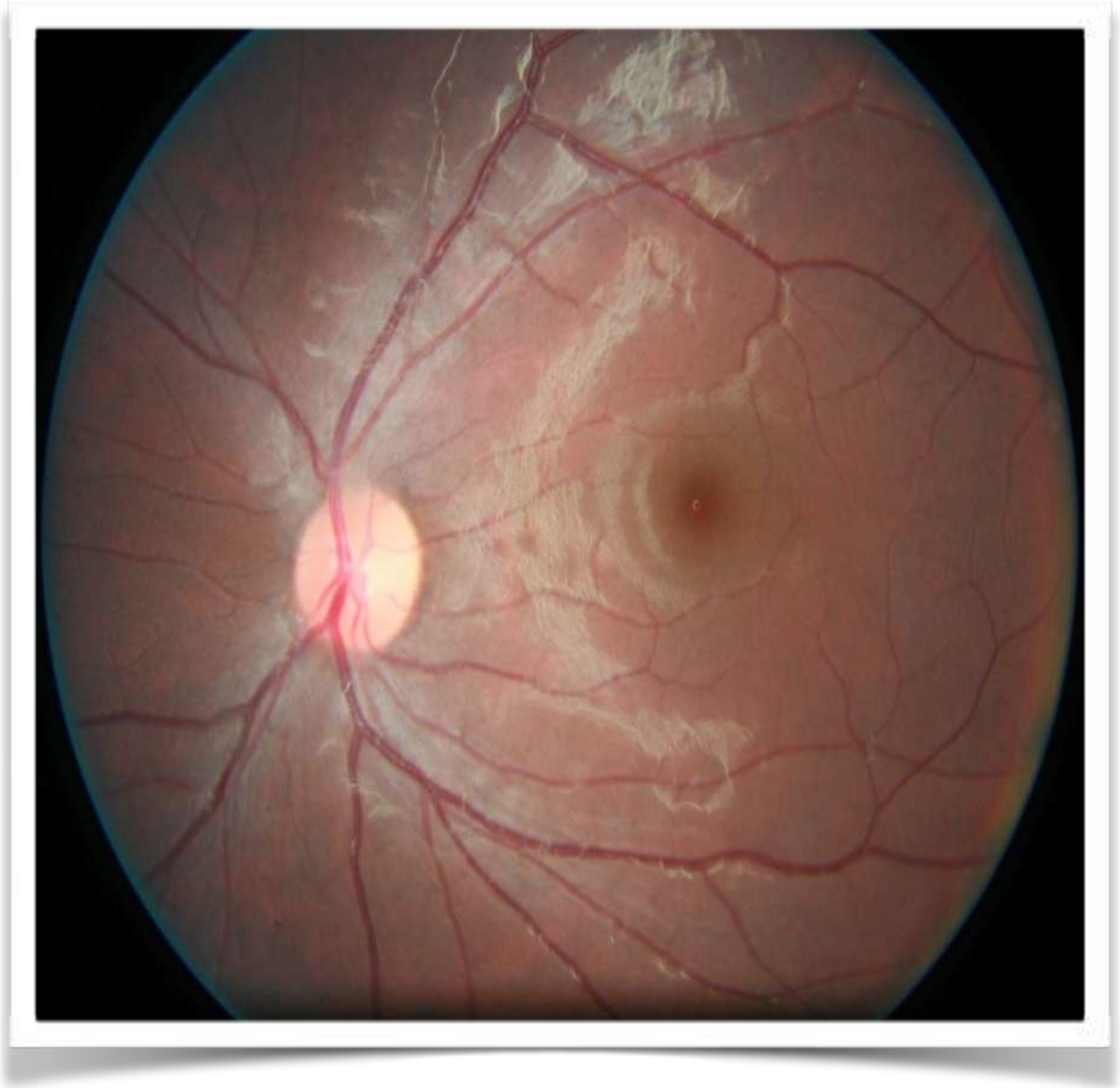
Classify into **healthy**, **mild** and **severe**

Labeling

1st doctor **2nd** doctor **3rd** doctor **4th** doctor

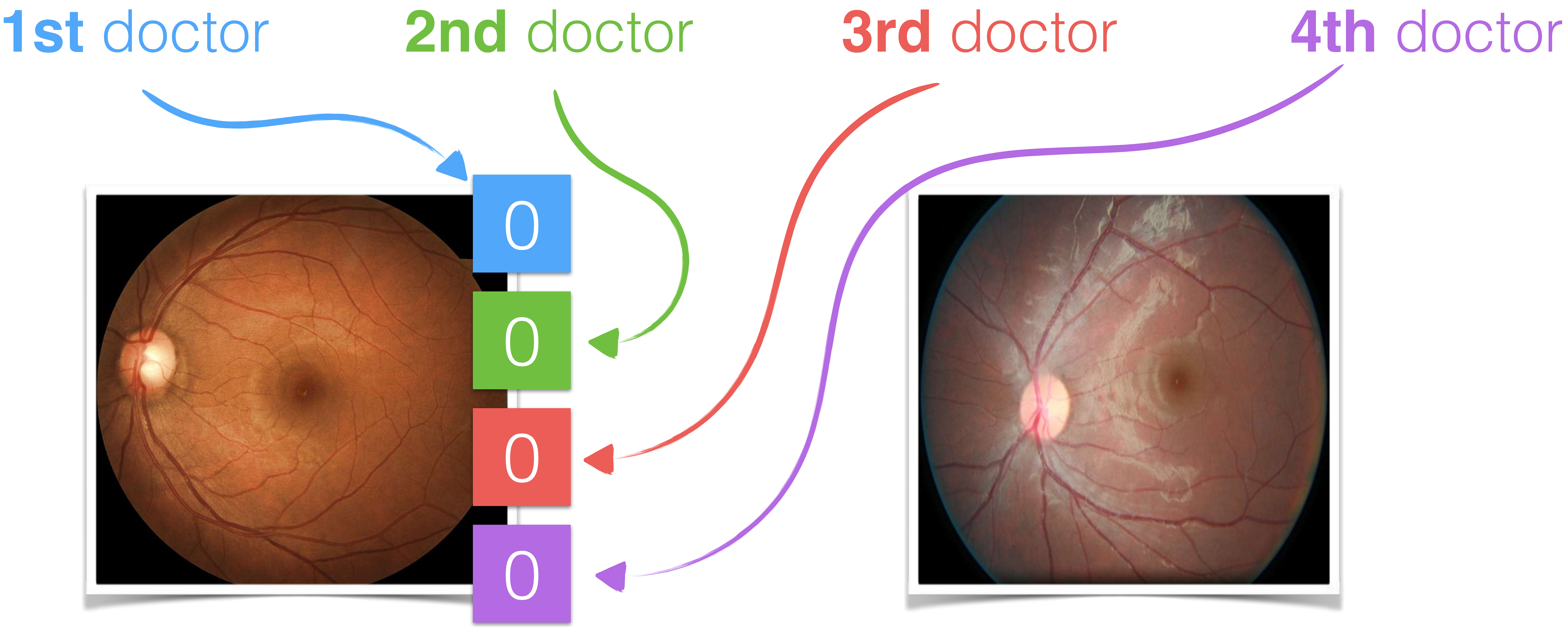


Healthy



Disease

Labeling



Healthy

Disease

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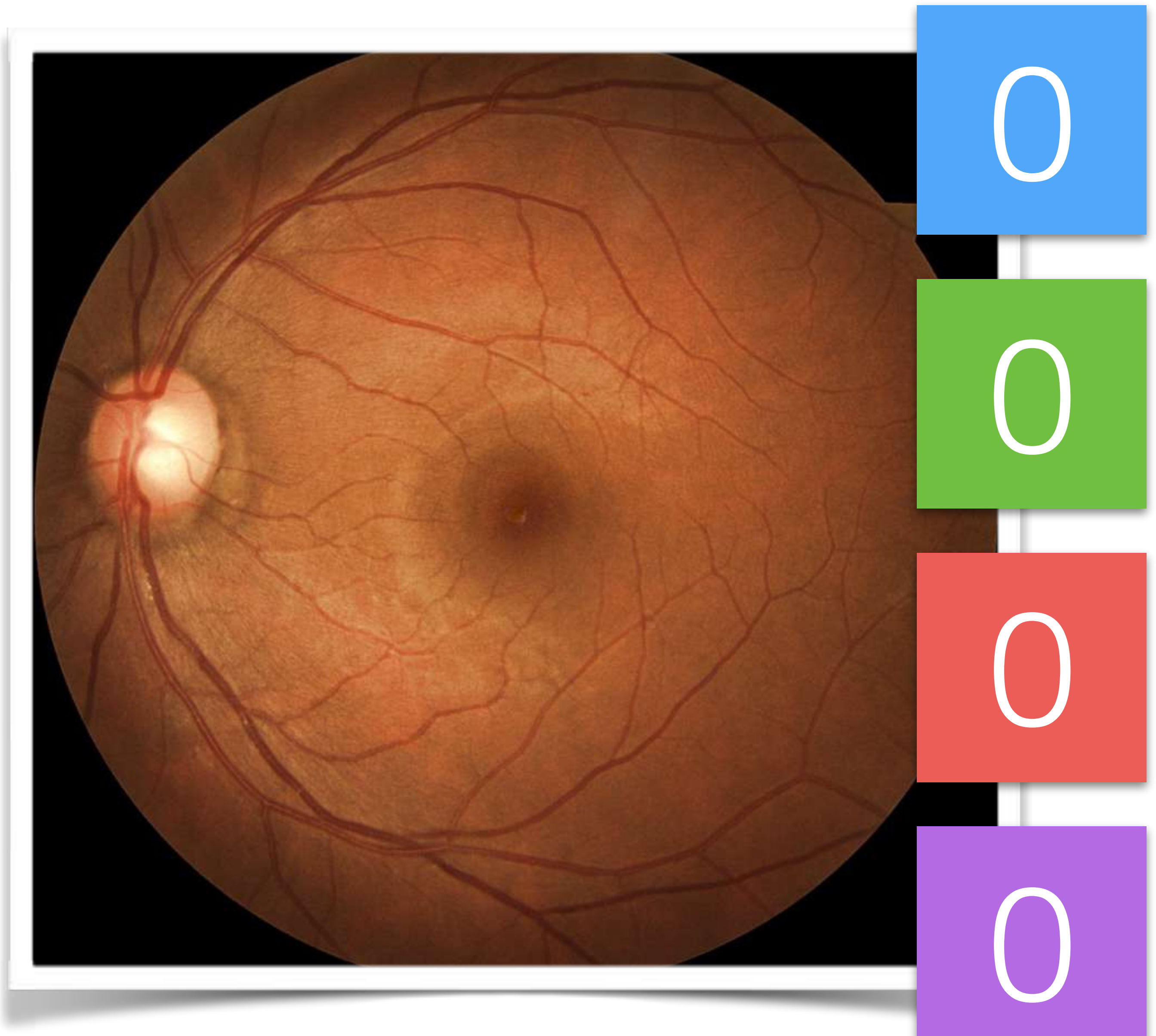
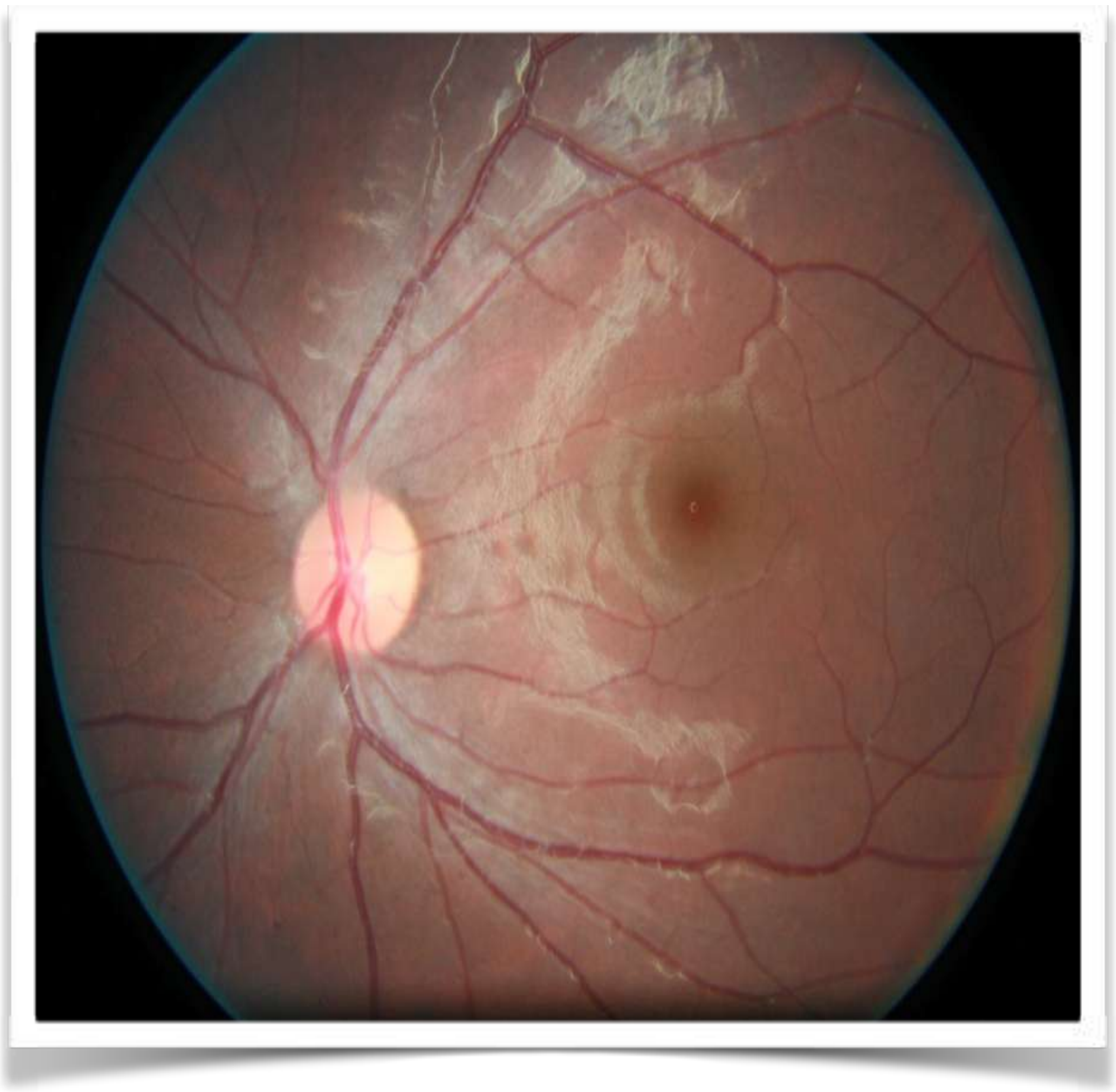


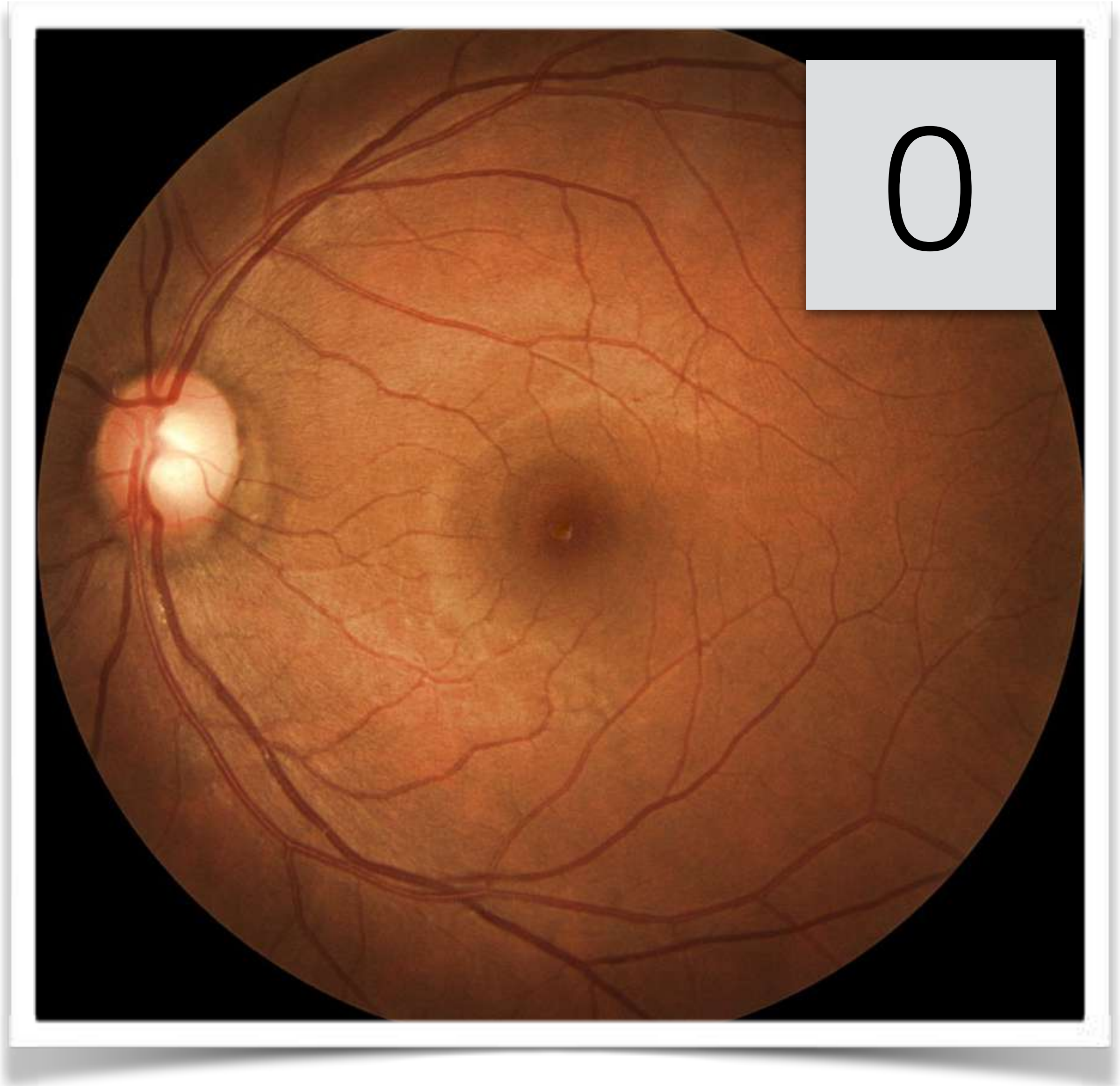
Healthy



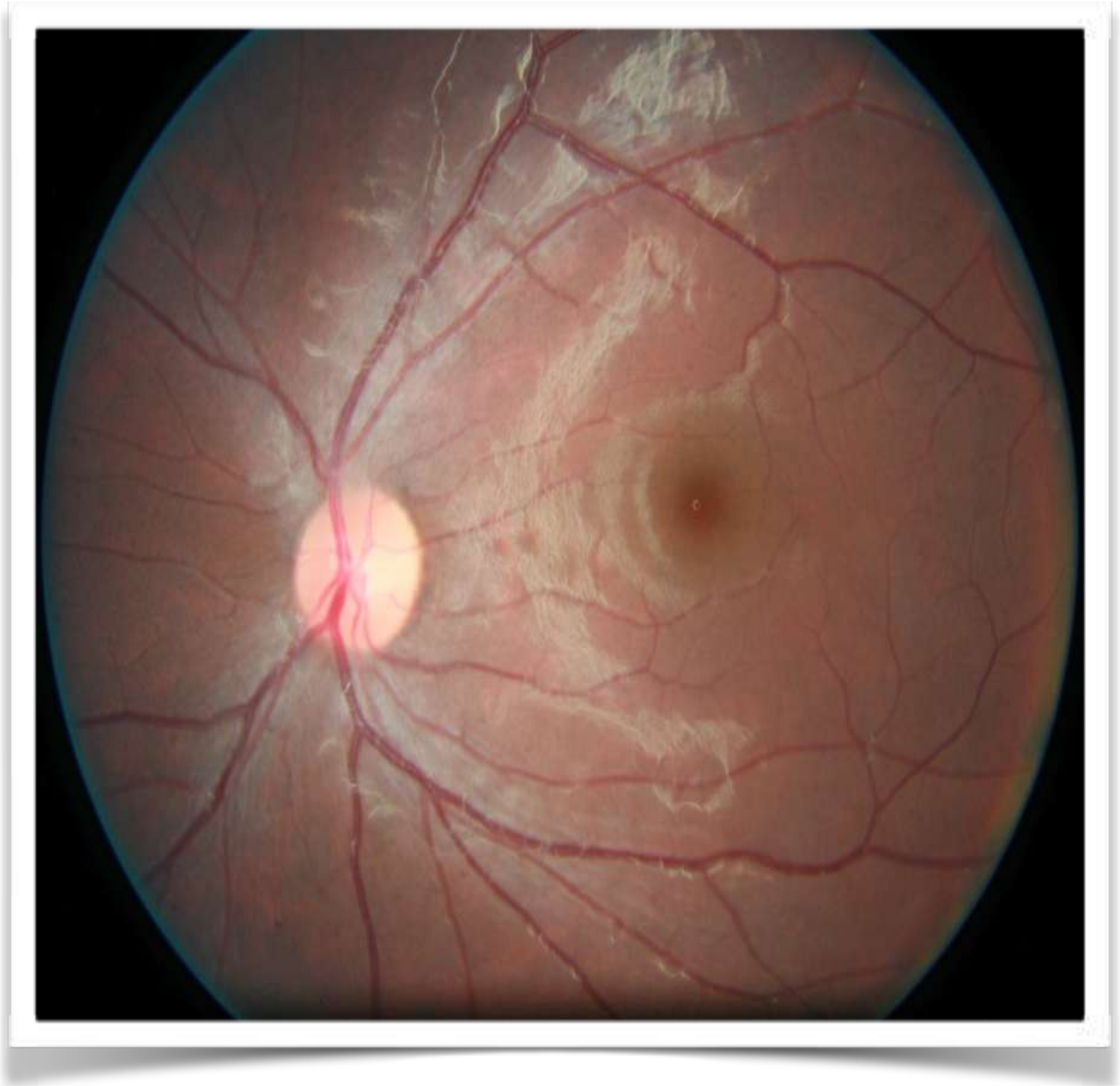
Disease

Labeling

1st doctor 2nd doctor 3rd doctor 4th doctor

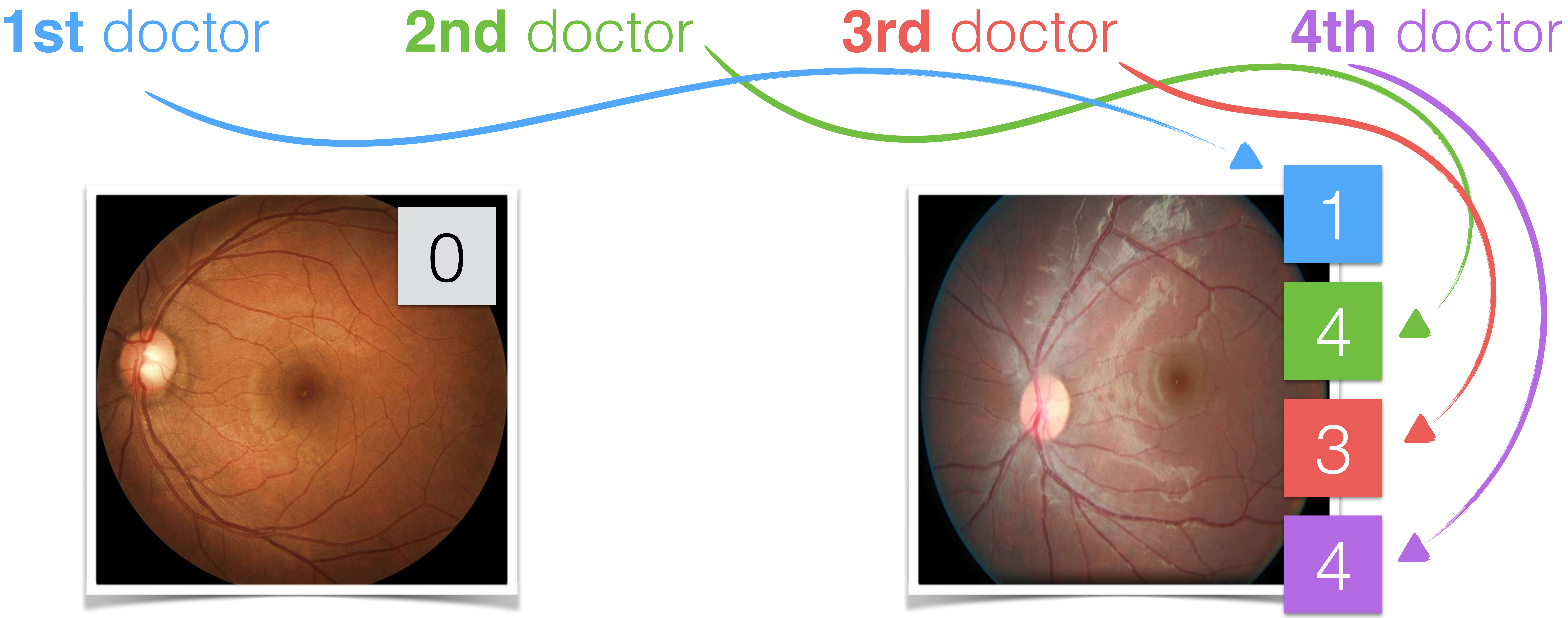


Healthy



Disease

Labeling



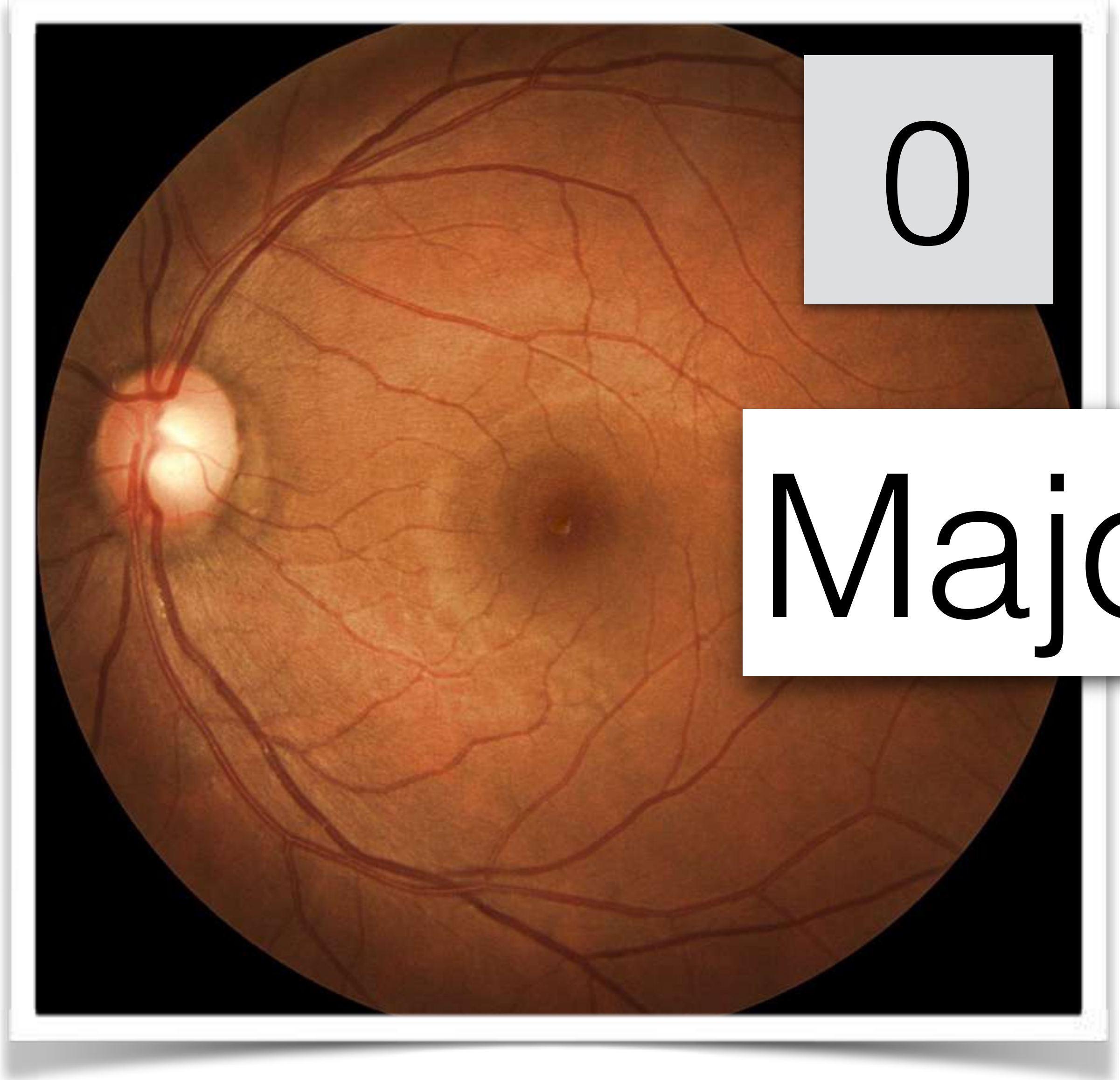
Healthy

Disease

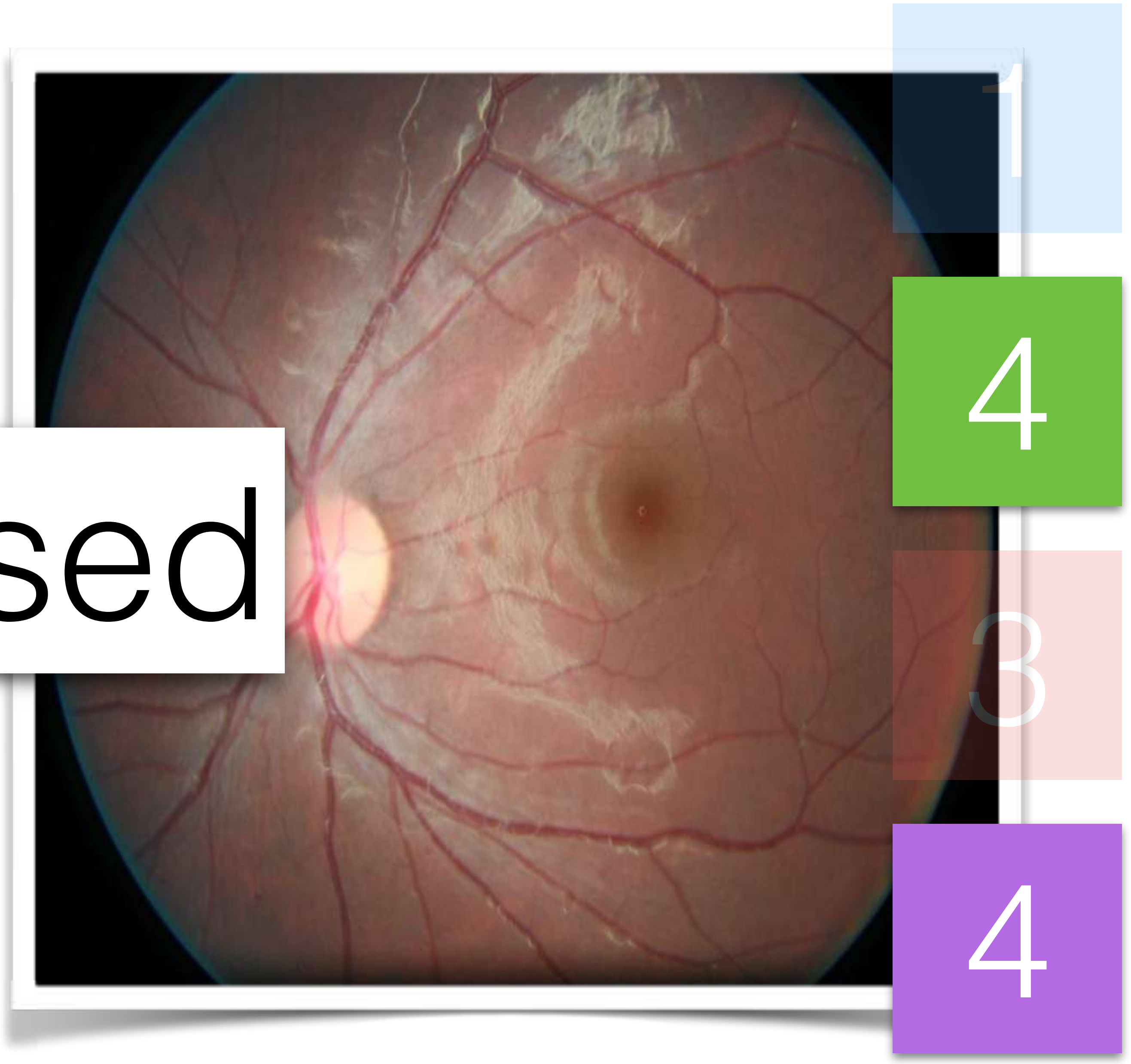
Labeling

1st doctor 2nd doctor 3rd doctor 4th doctor

Major vote is used



Healthy



Disease

Labeling

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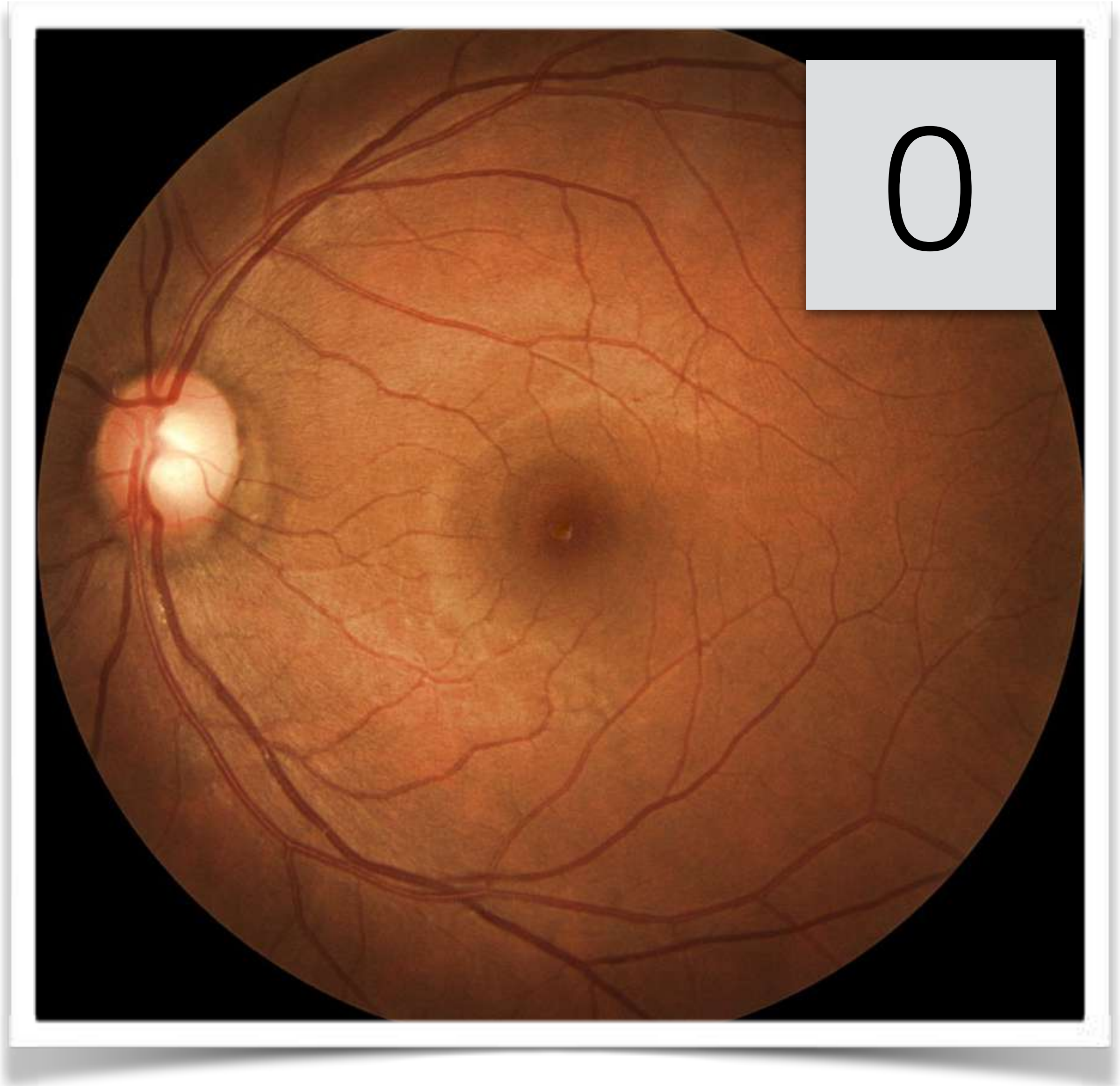

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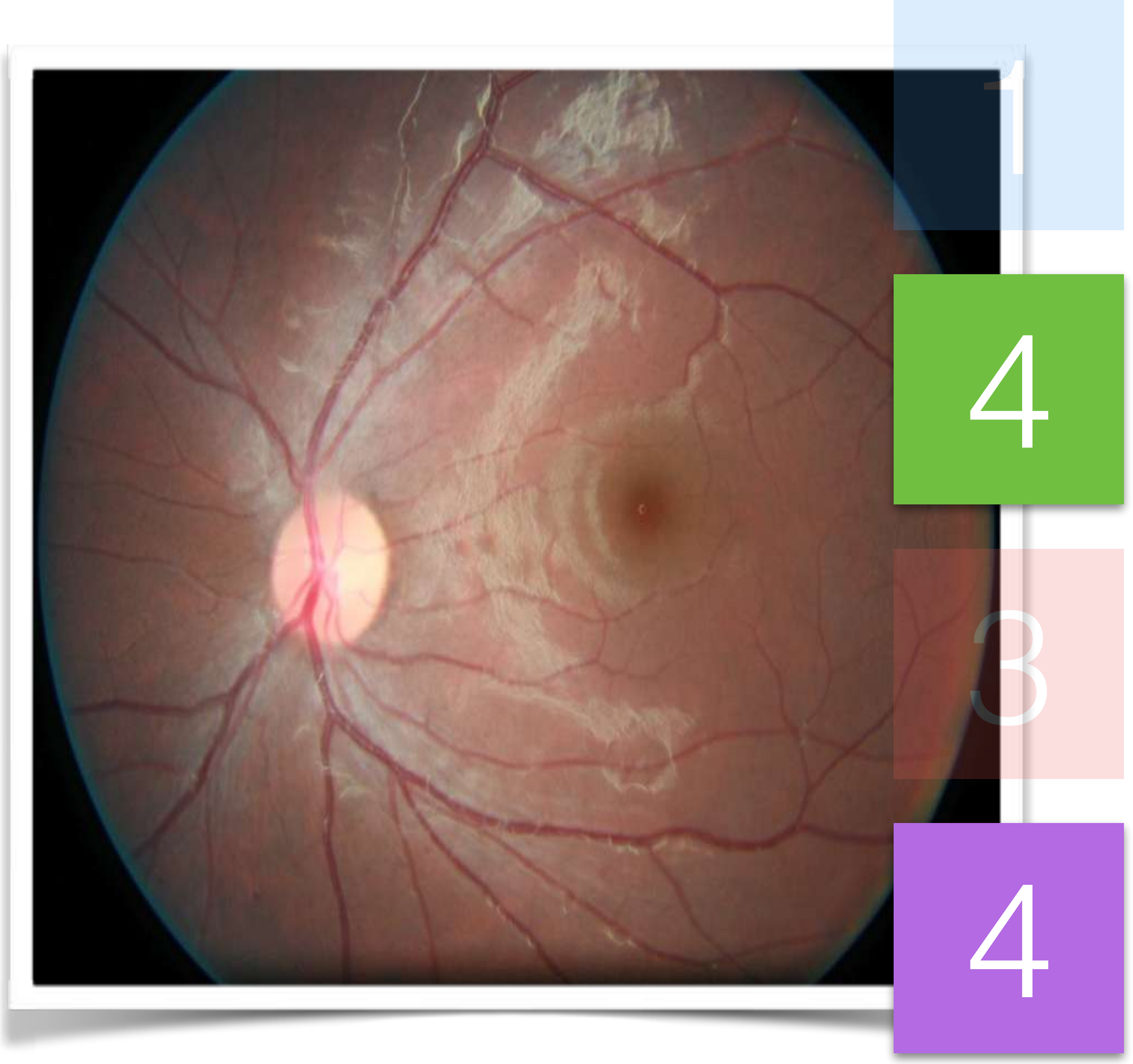

Disease

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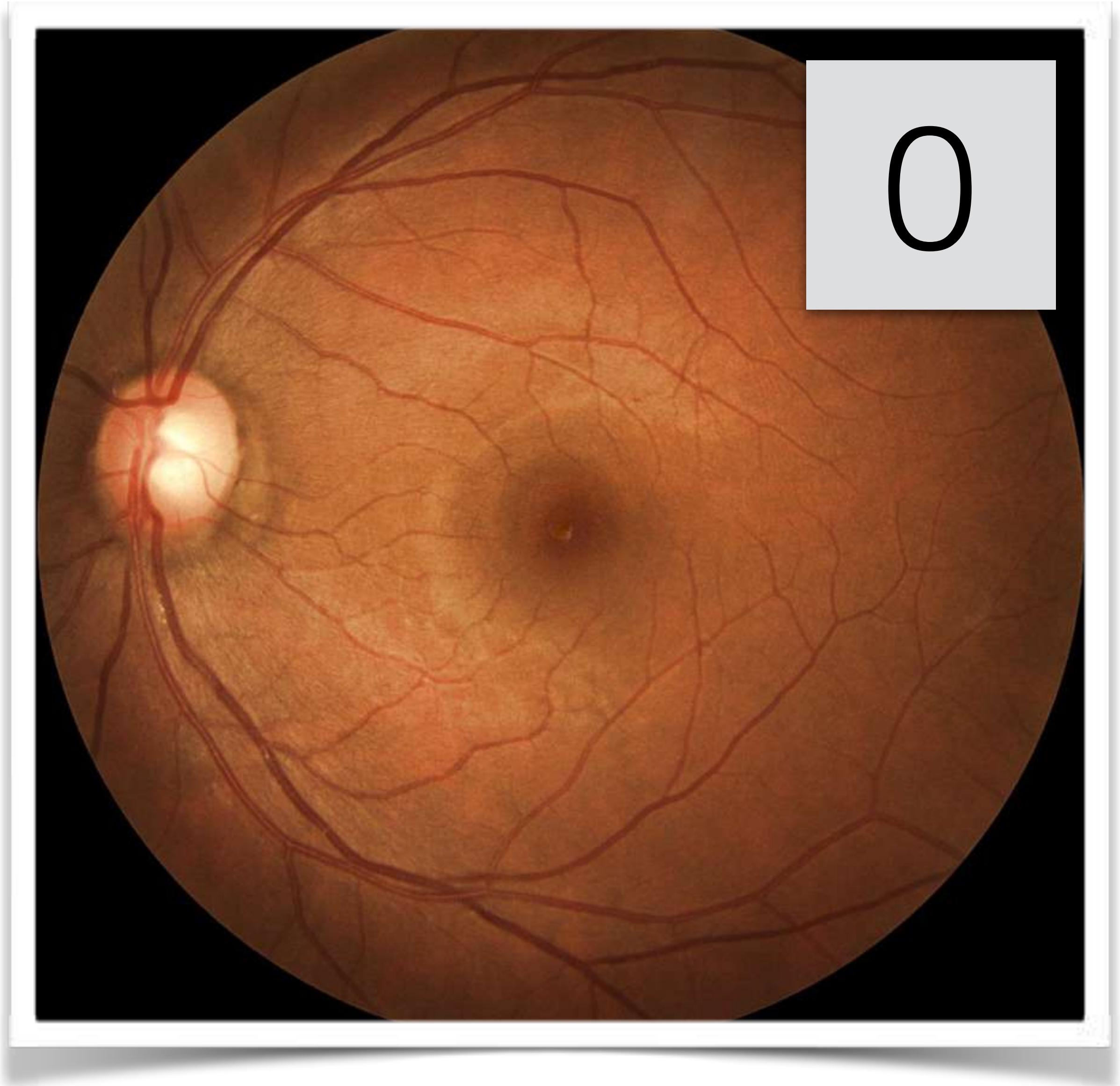
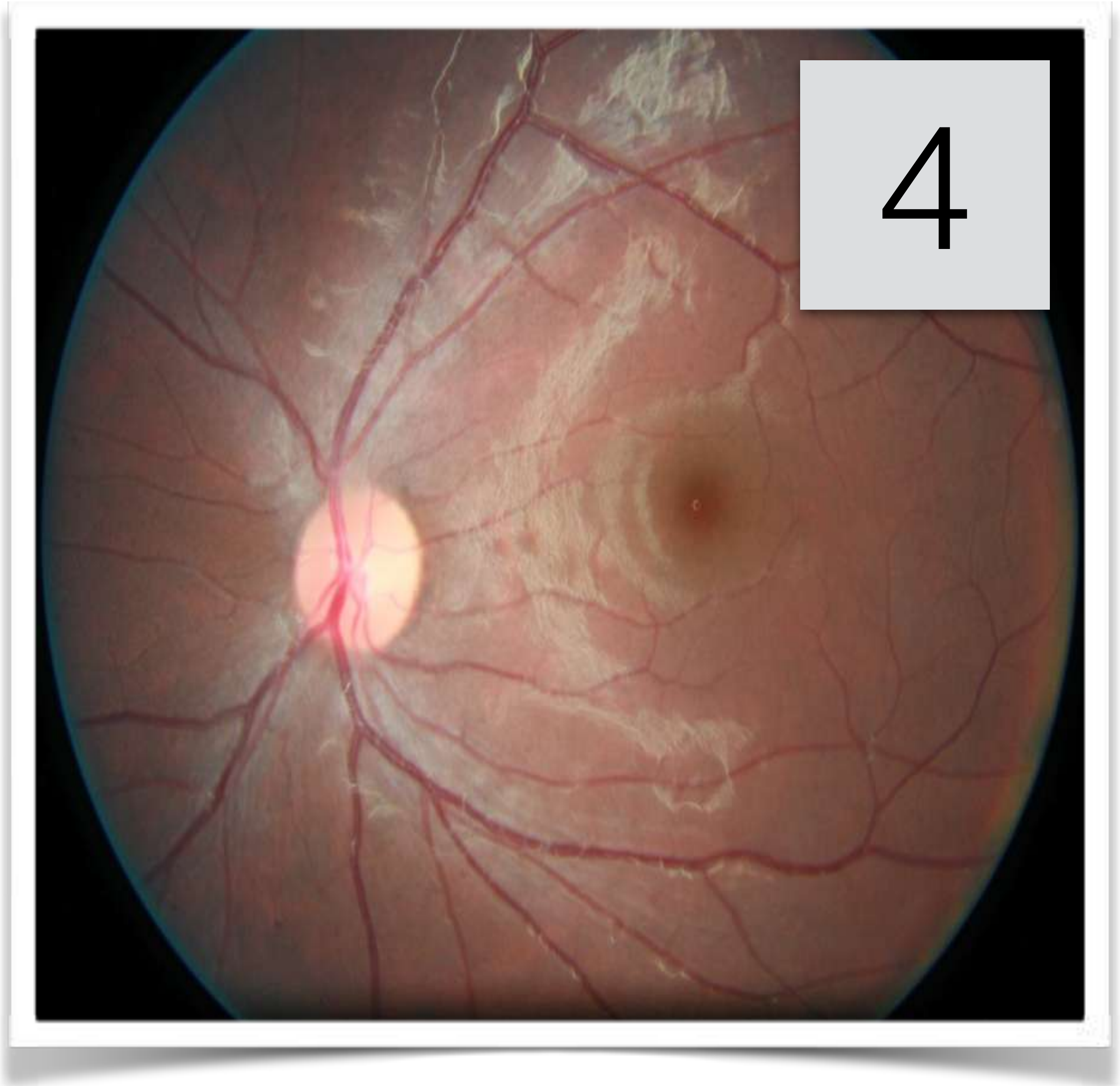


Healthy



Disease

Labeling

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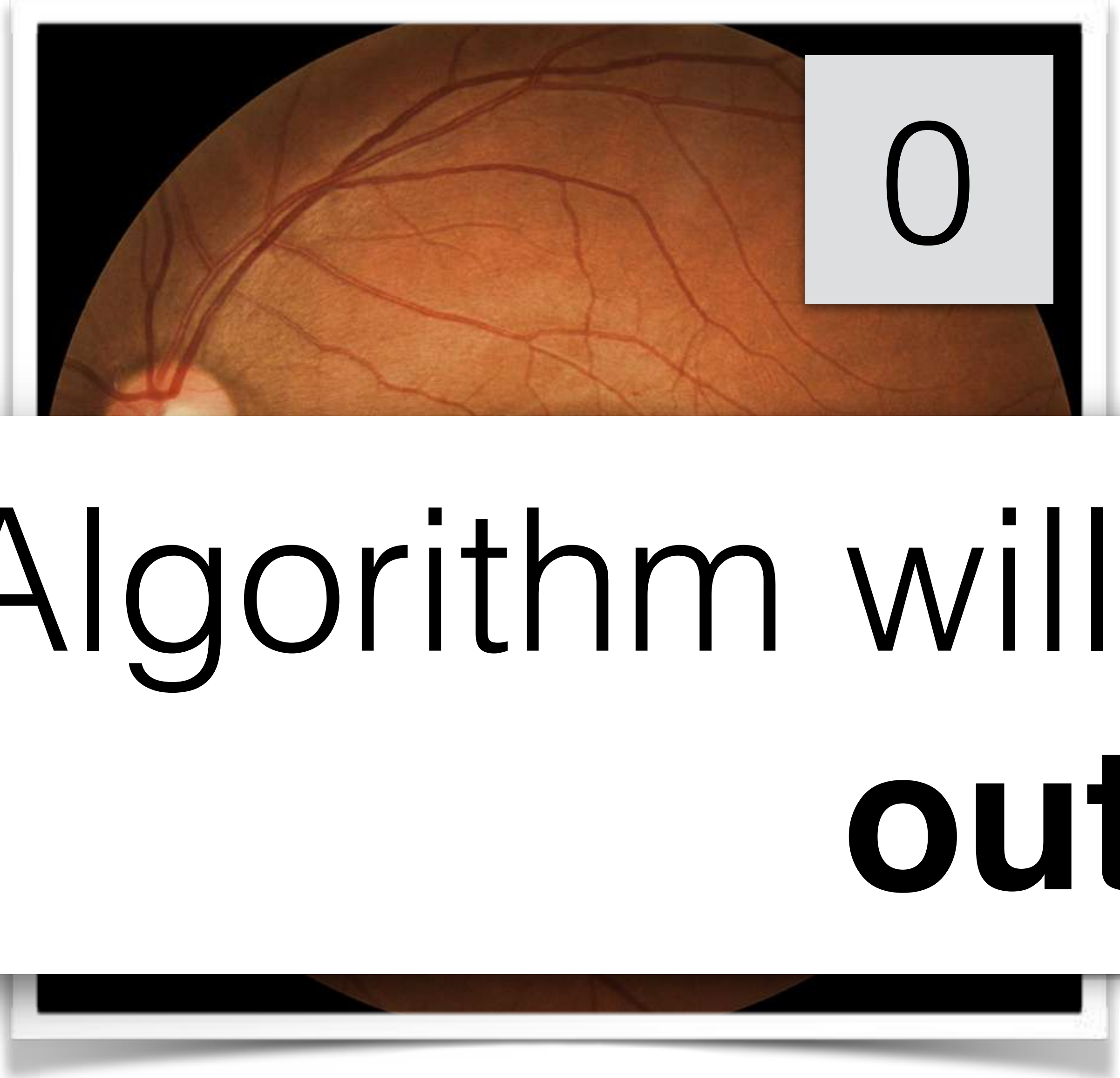
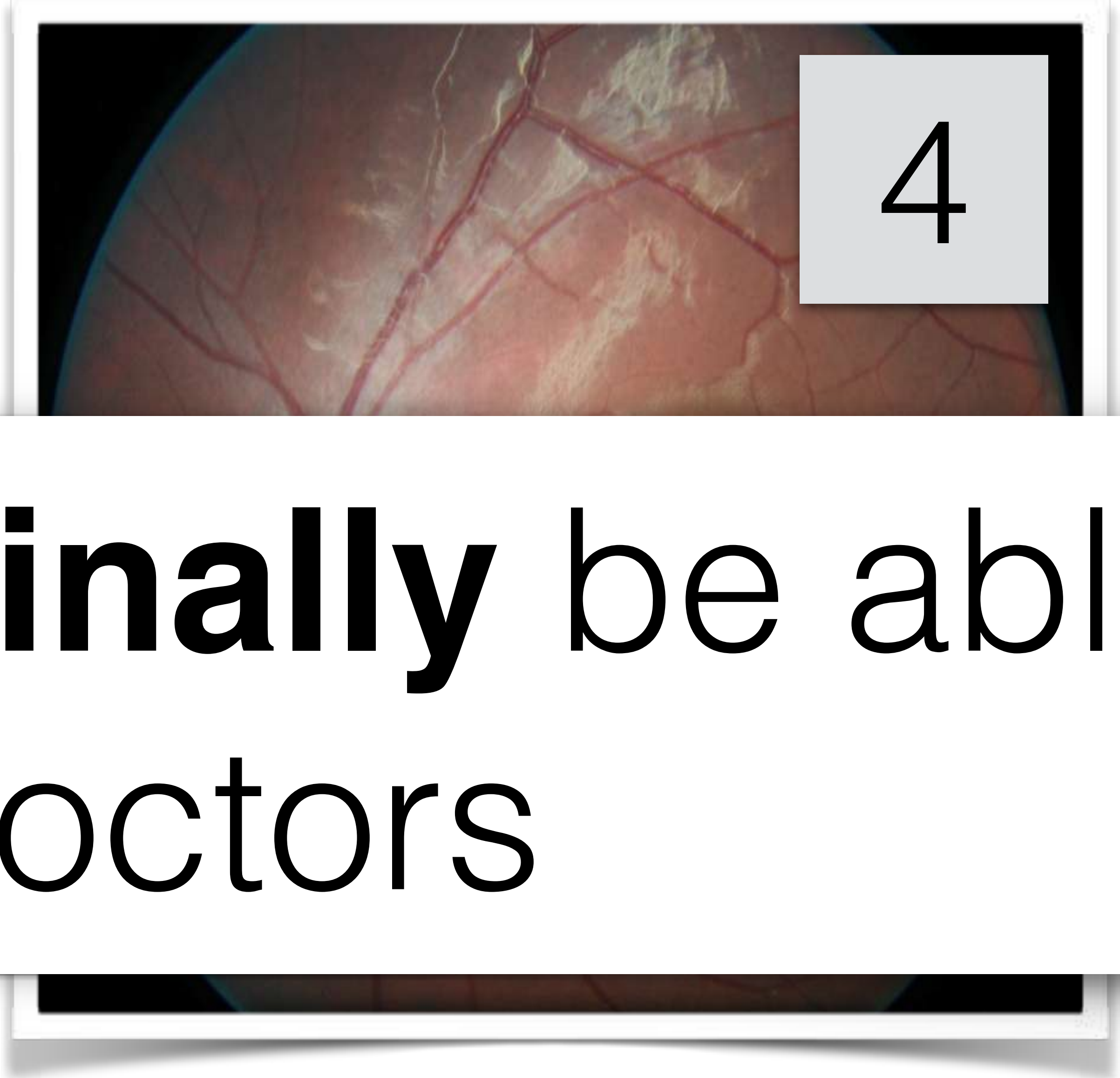


Healthy

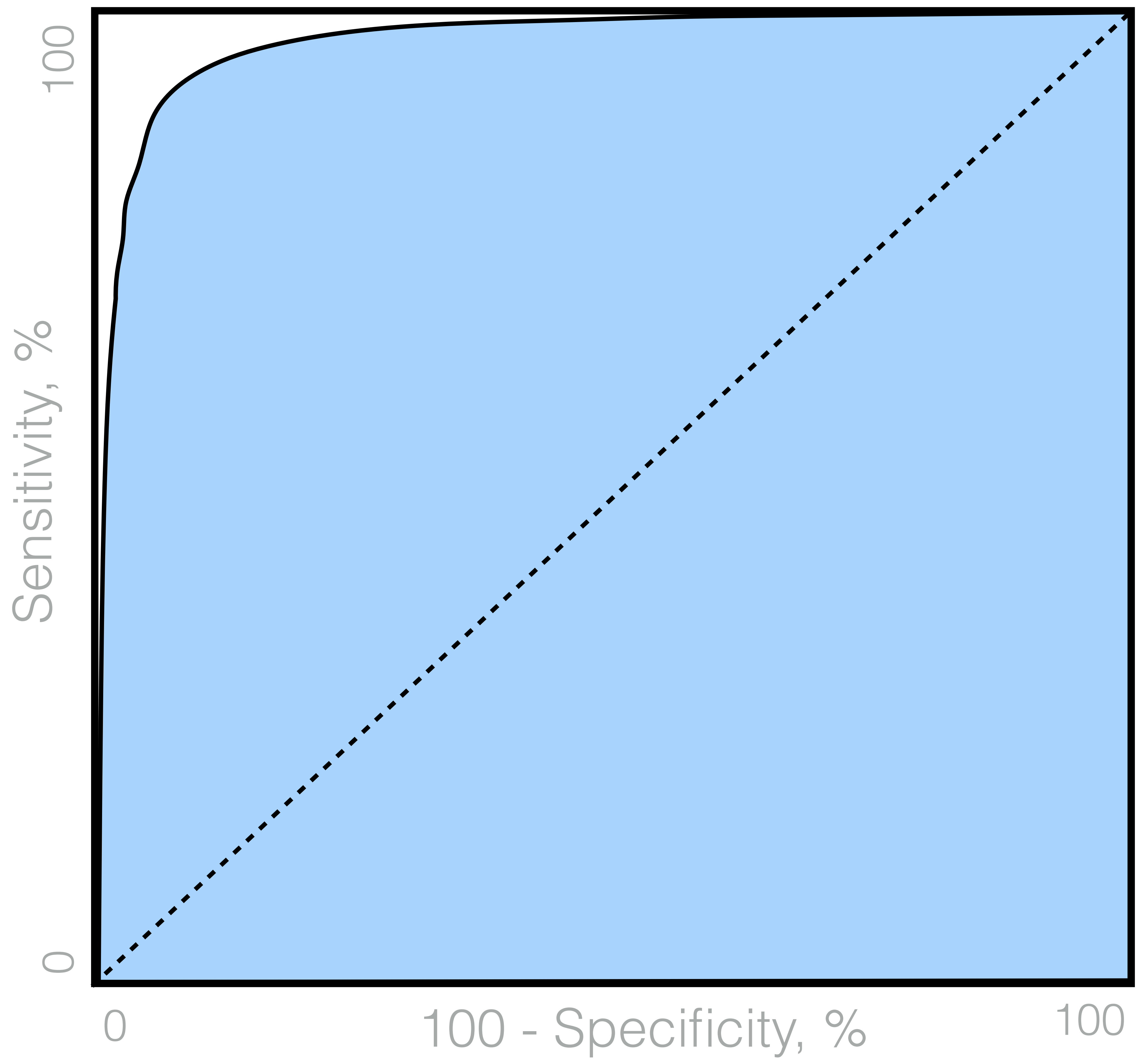


Disease

Algorithm will only **marginally** be able to **outperform** doctors

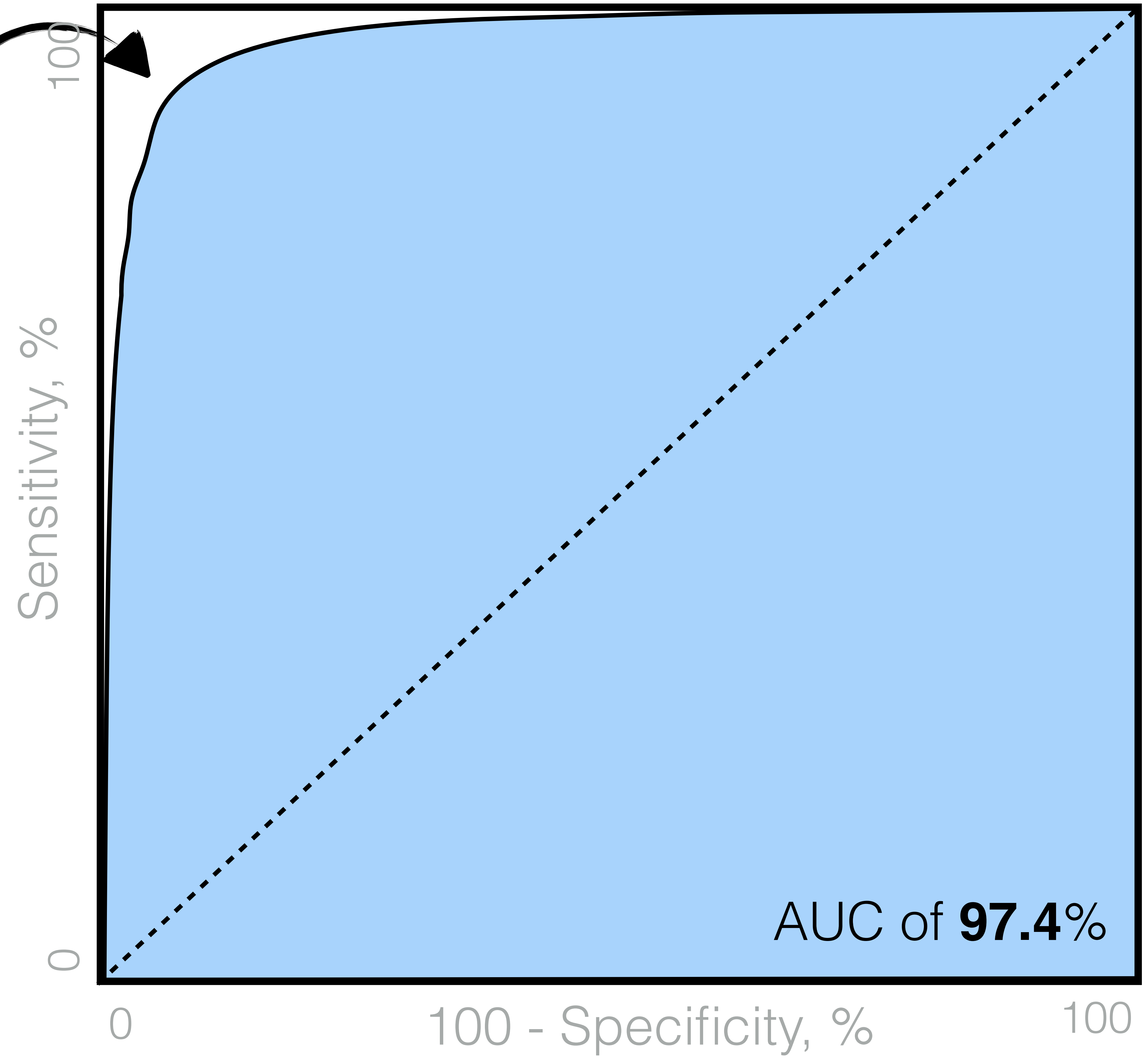
Algorithm vs Ophthalmologists

Algorithm vs Ophthalmologists



Algorithm vs Ophthalmologists

The black curve is ROC for the **Deep Learning algorithm**



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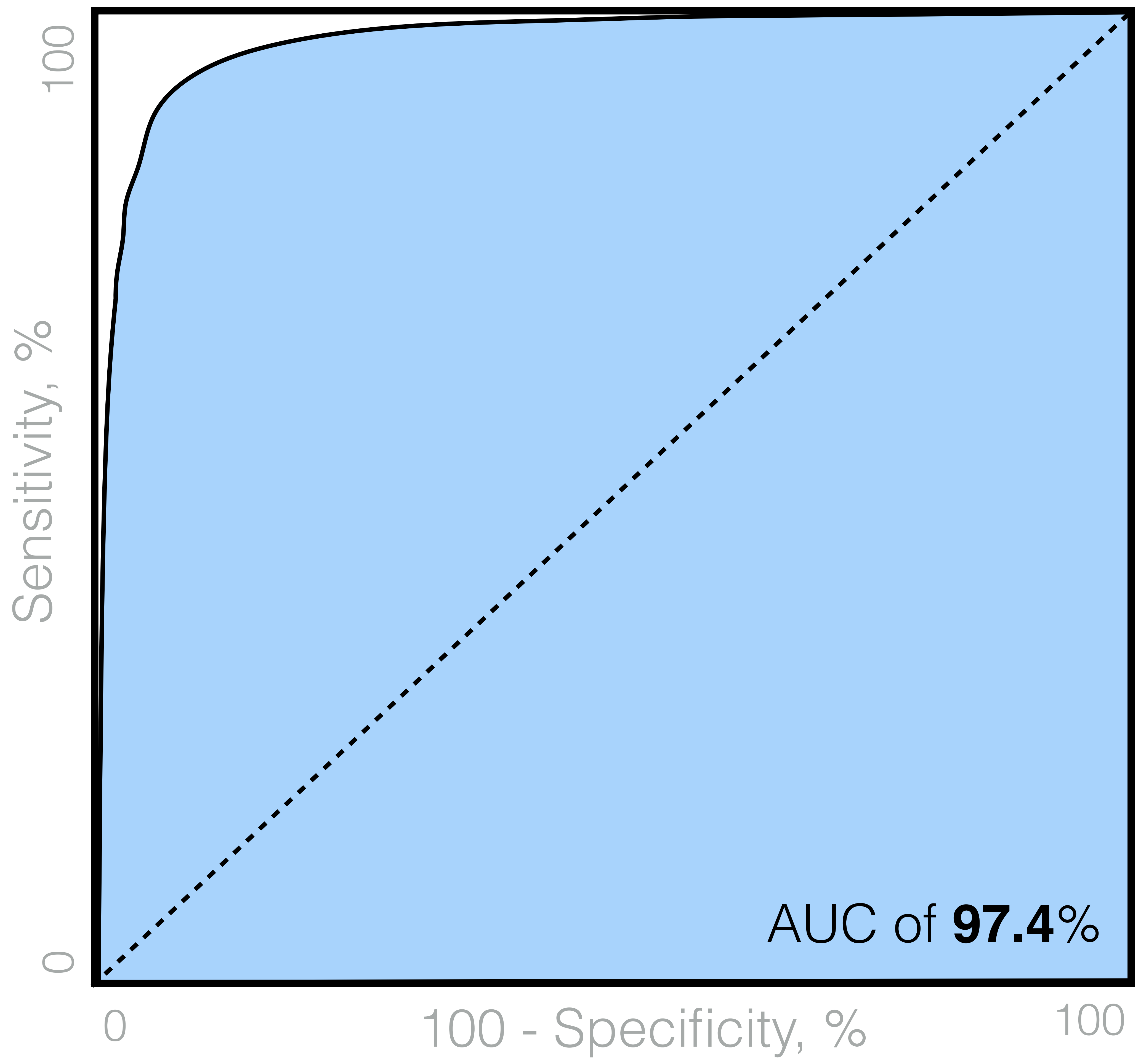
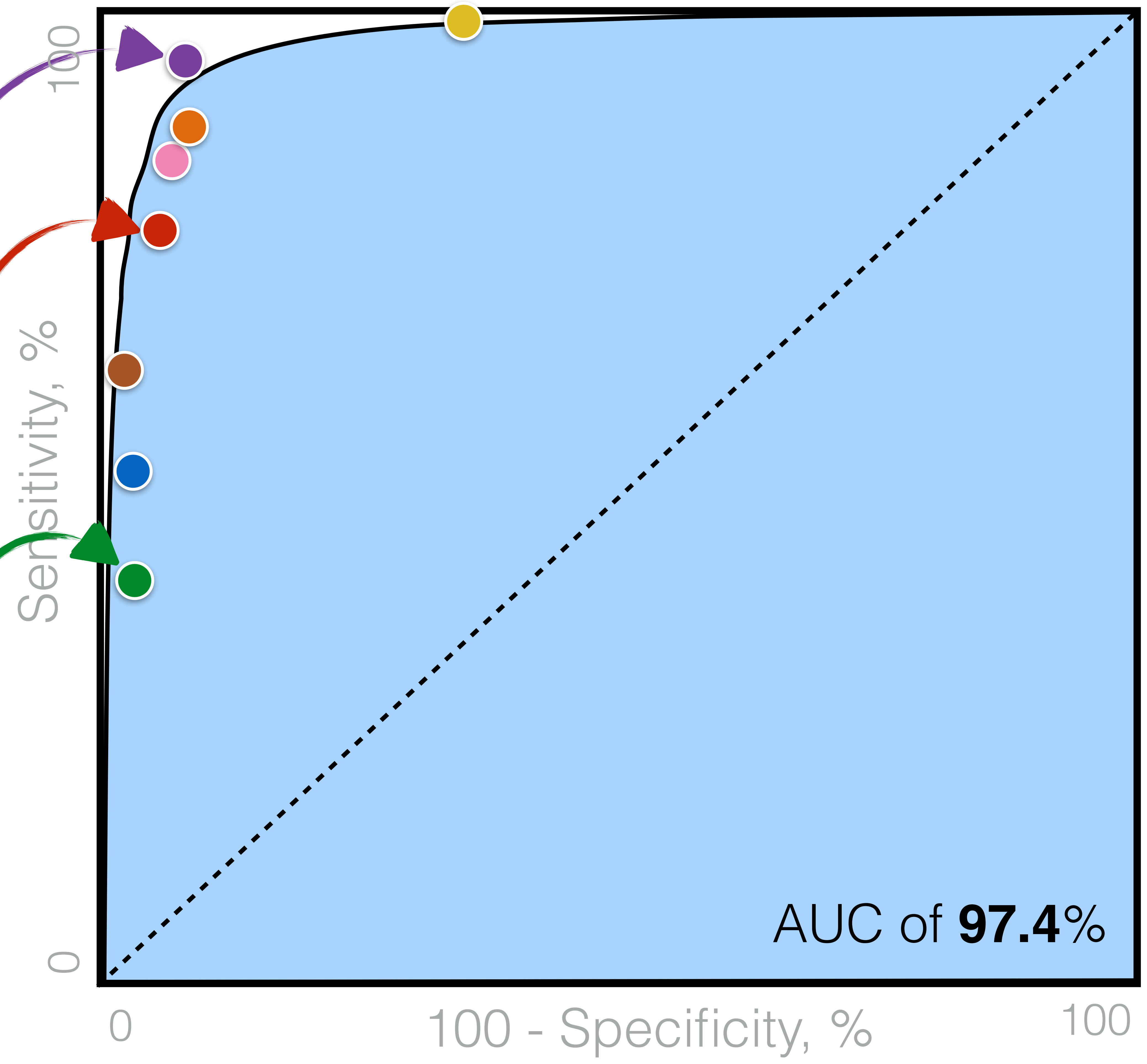


Algorithm vs Ophthalmologists

The black curve is ROC for the **Deep Learning algorithm**

Points on ROC are performances of individual **ophthalmologists**

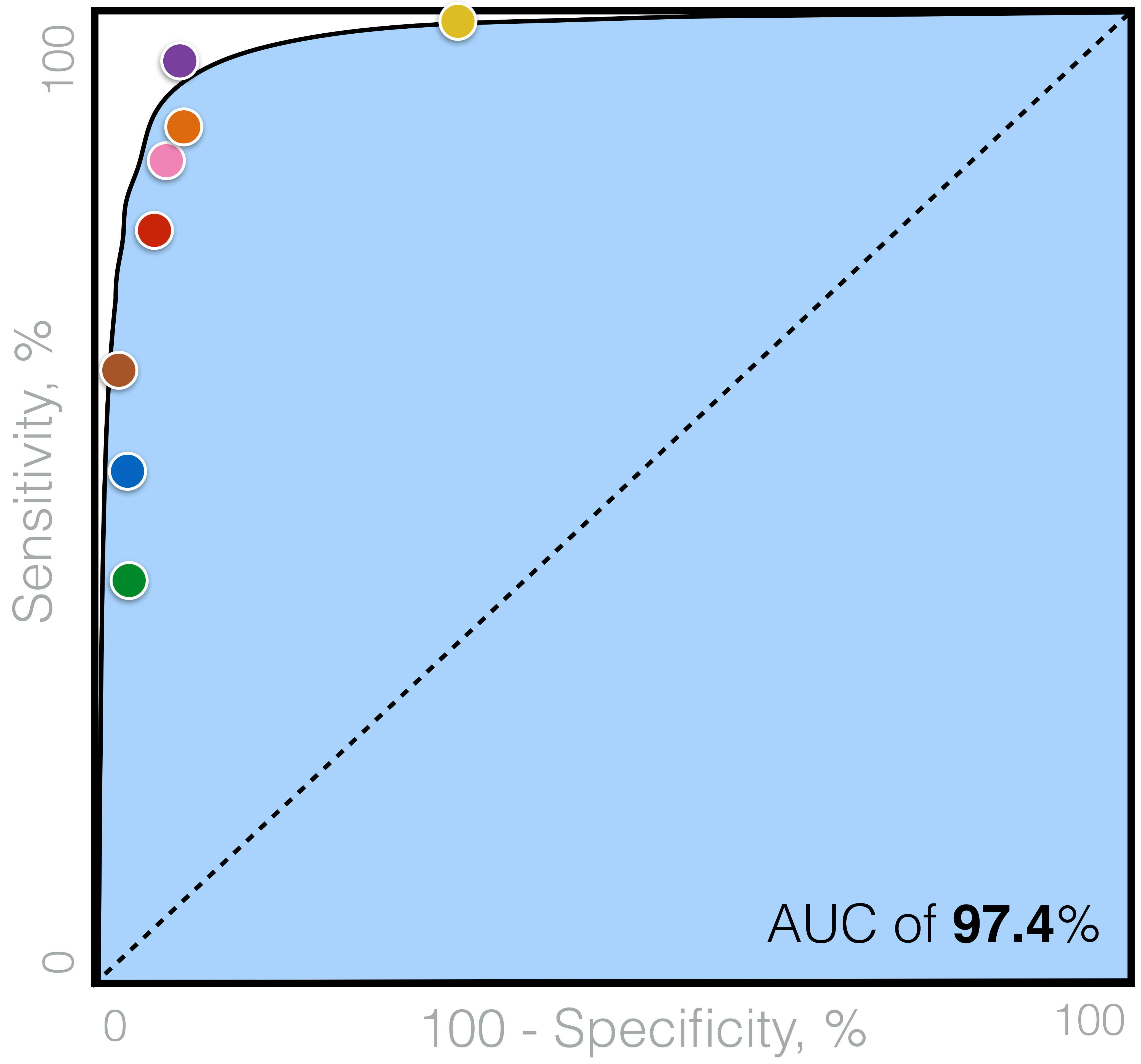


Algorithm vs Ophthalmologists

The black curve is ROC for the **Deep Learning algorithm**

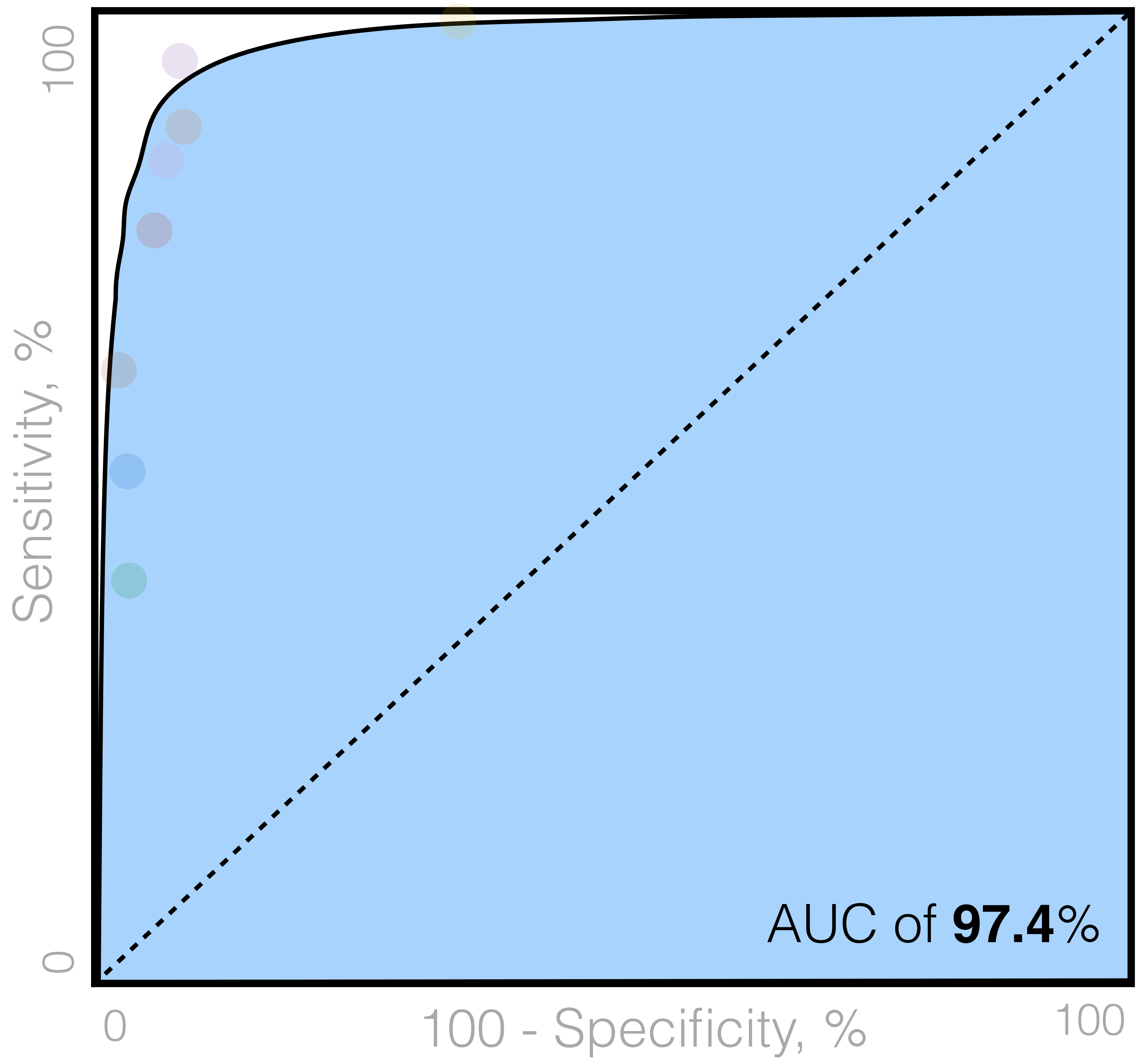
Points on ROC are performances of individual **ophthalmologists**

Performances are very **similar**



Algorithm vs Ophthalmologists

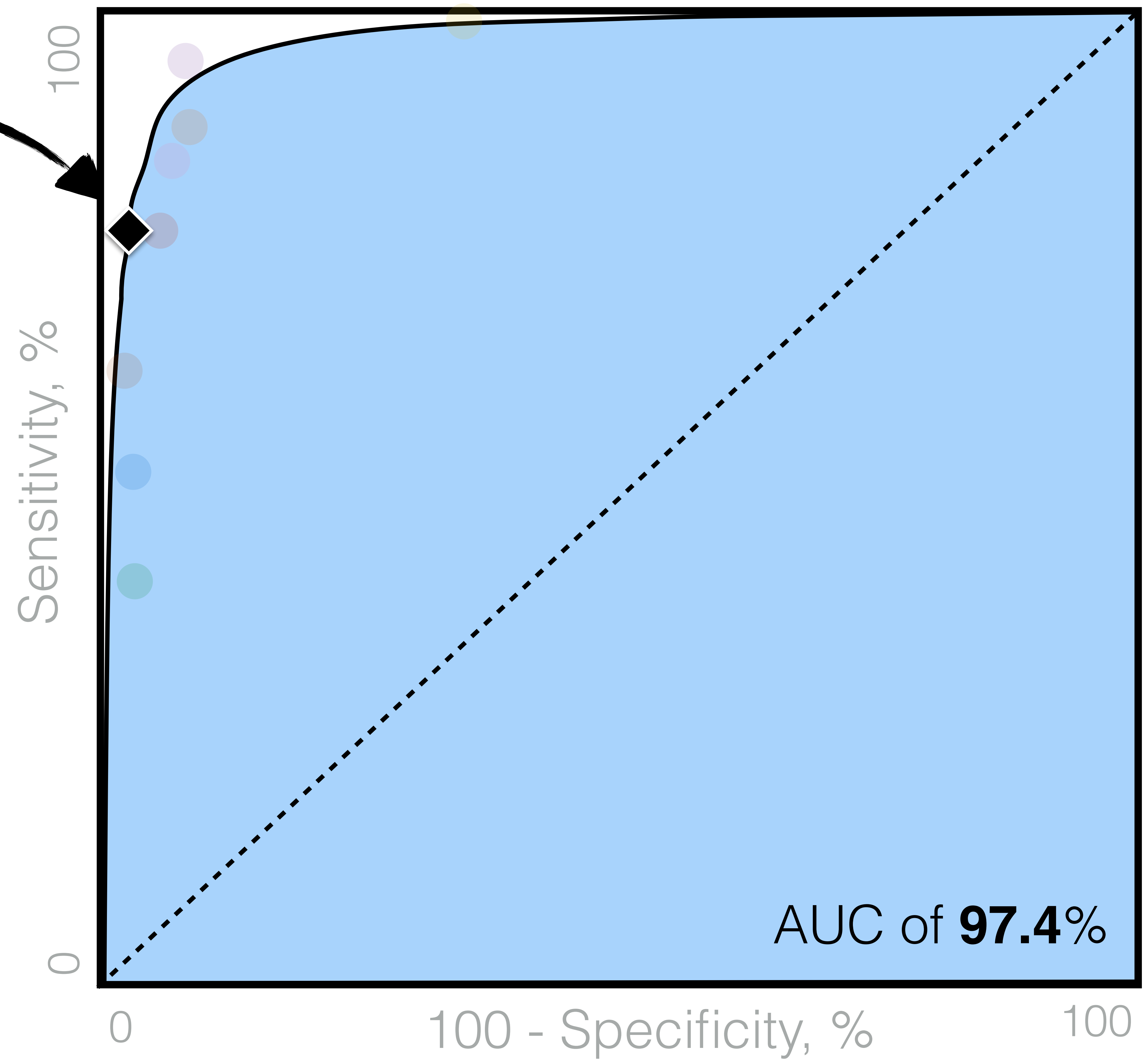
Deep Learning algorithm can operate in **any point** on the **curve**



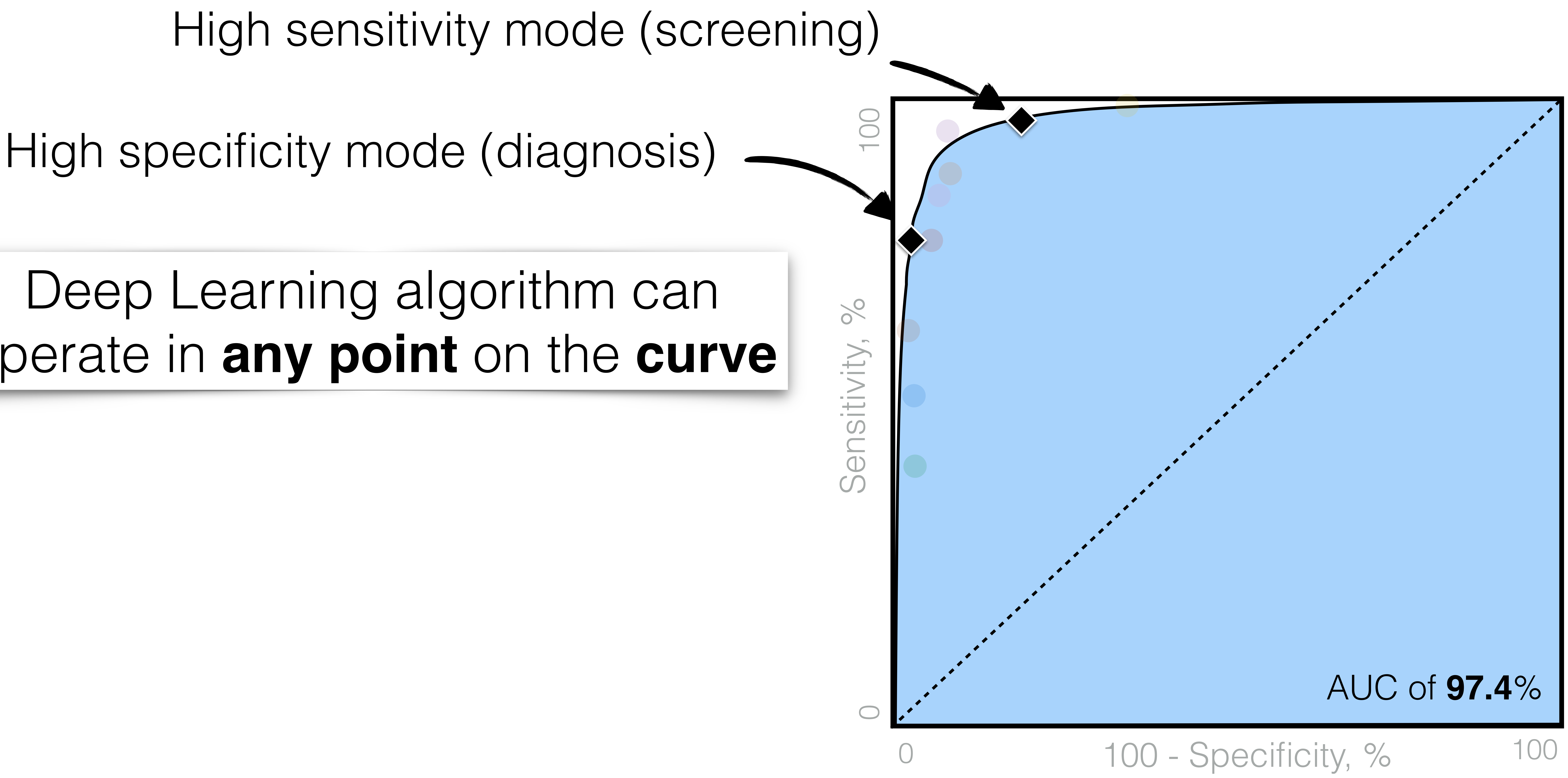
Algorithm vs Ophthalmologists

High specificity mode (diagnosis)

Deep Learning algorithm can operate in **any point** on the **curve**



Algorithm vs Ophthalmologists

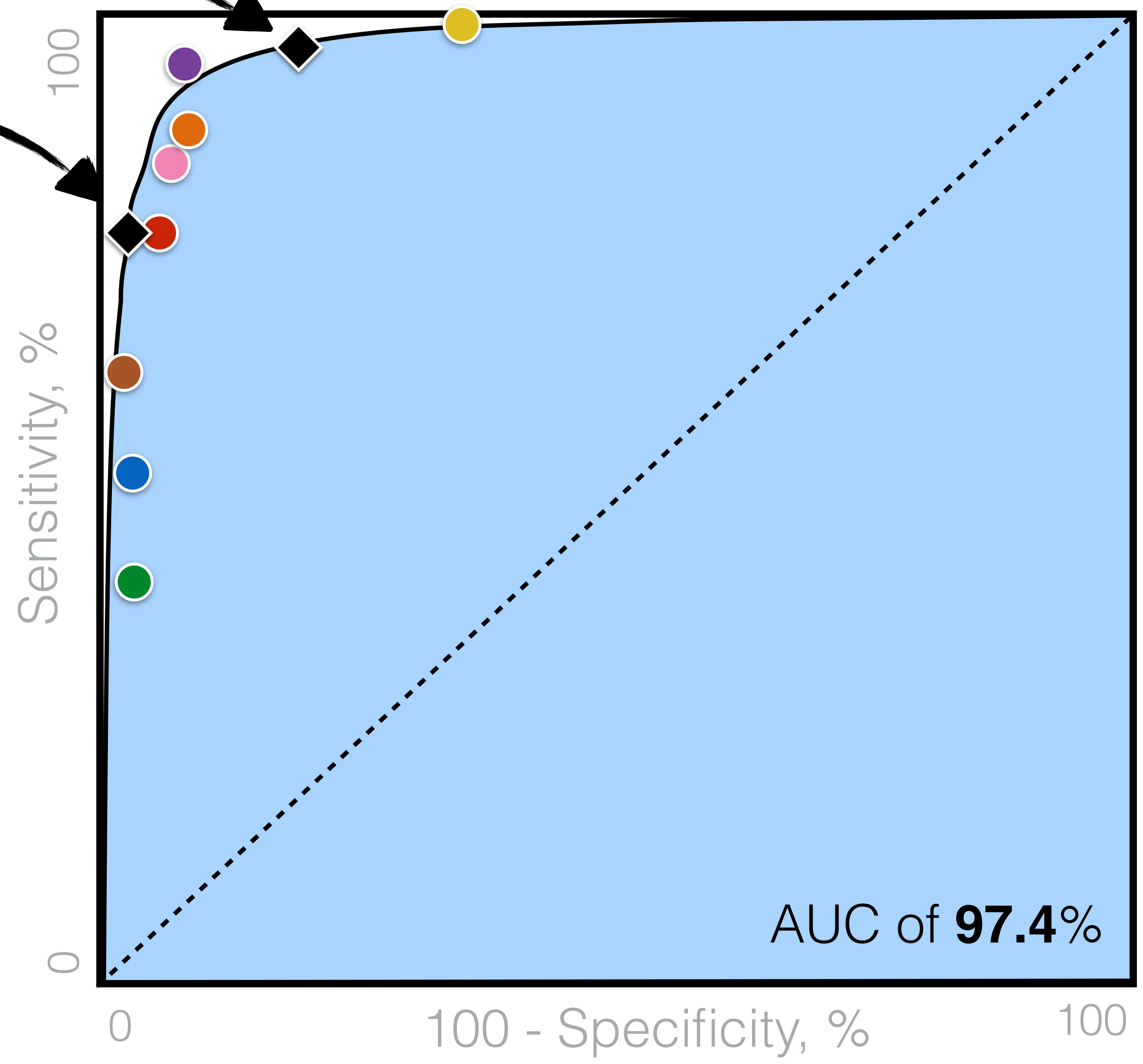


Deep Learning algorithm can operate in **any point** on the **curve**

Algorithm vs Ophthalmologists

High sensitivity mode (screening)

High specificity mode (diagnosis)



Deep Learning algorithm can operate in **any point** on the **curve**

While **ophthalmologists**'s mode is **fixed** by experience

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Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs

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Dermatologist-level classification of skin cancer with deep neural networks

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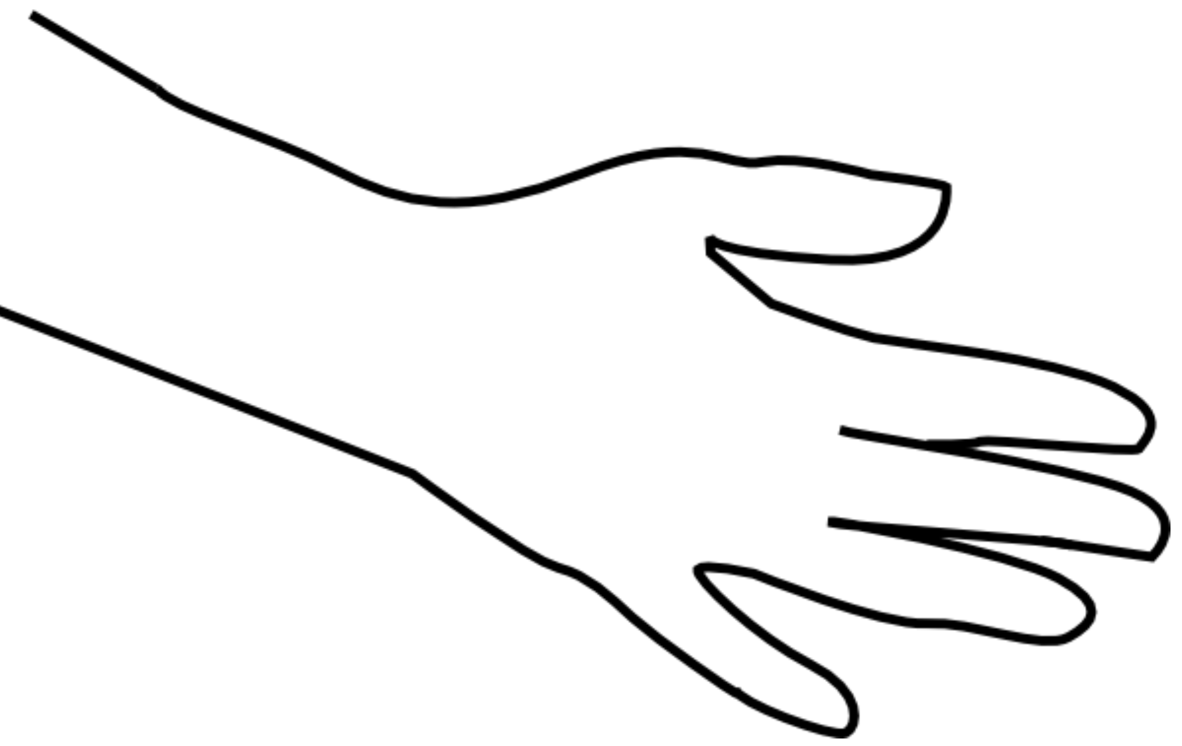
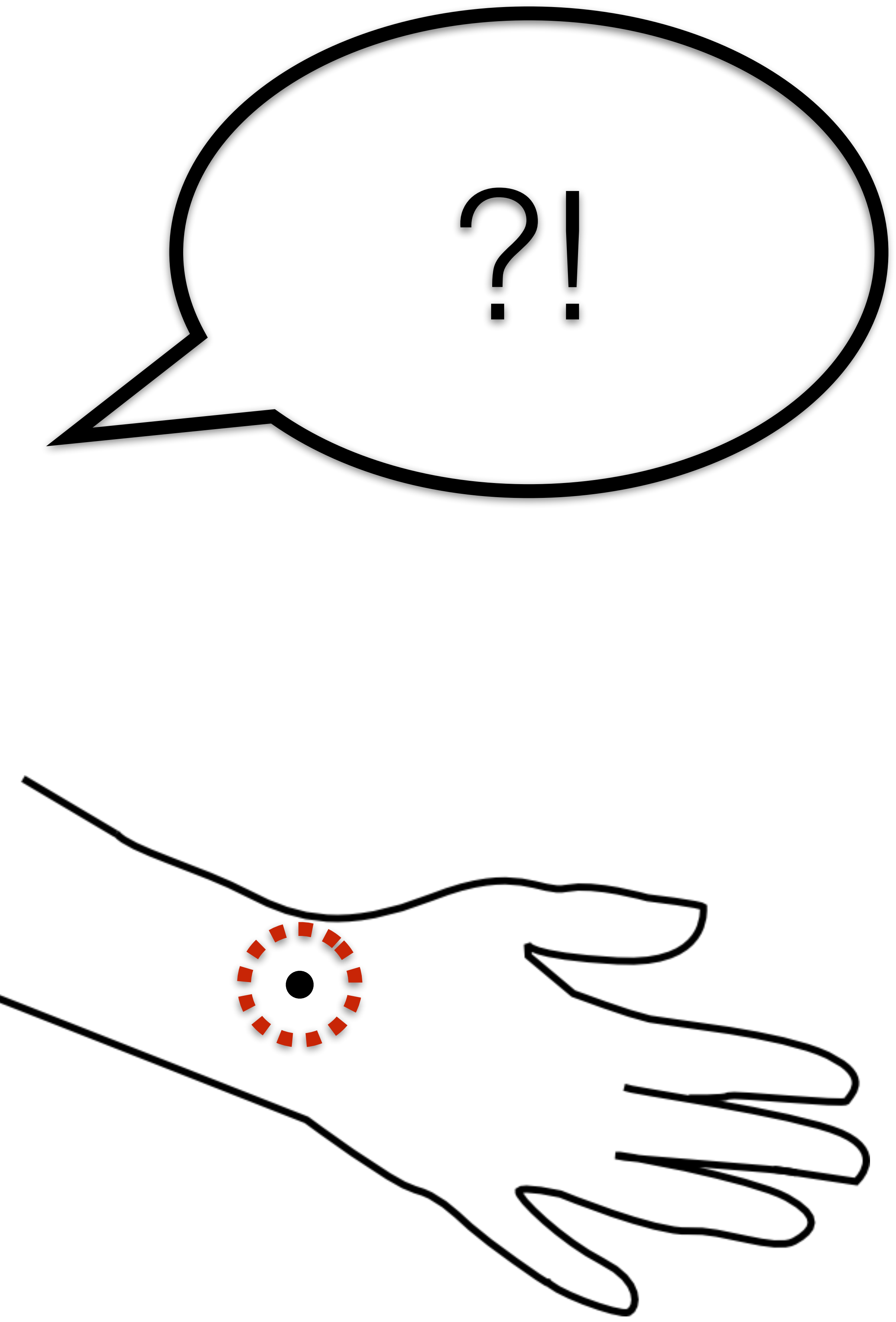
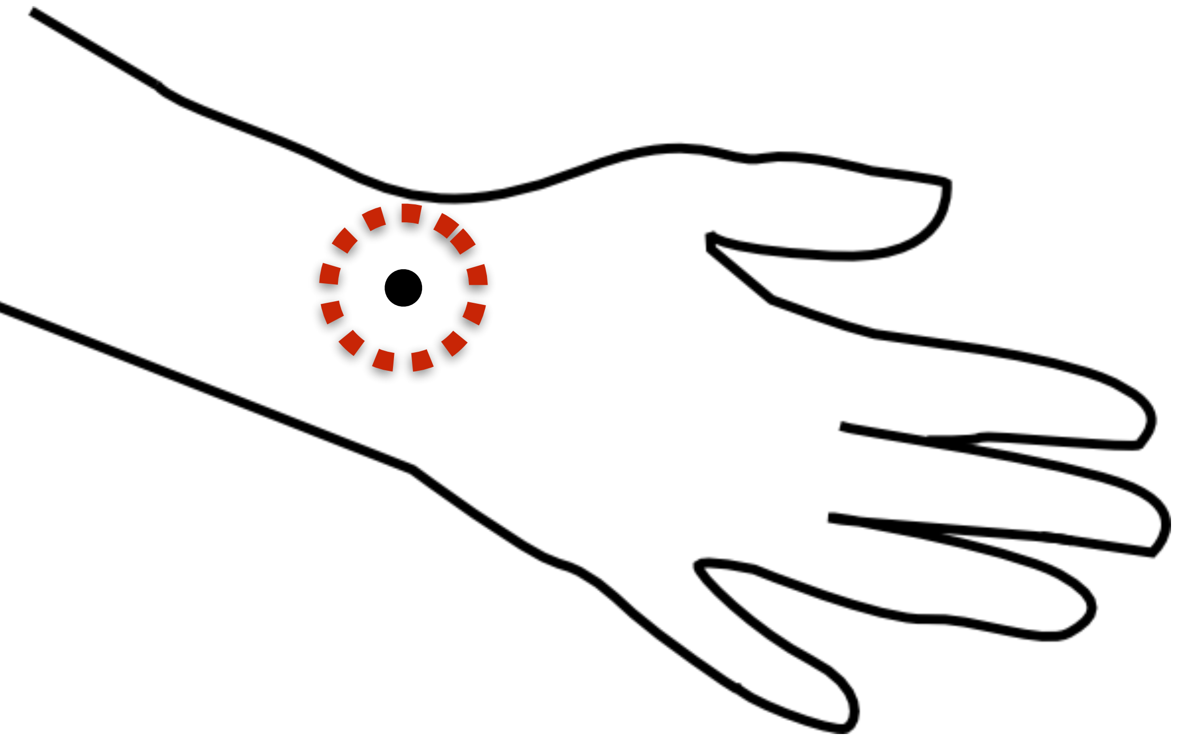
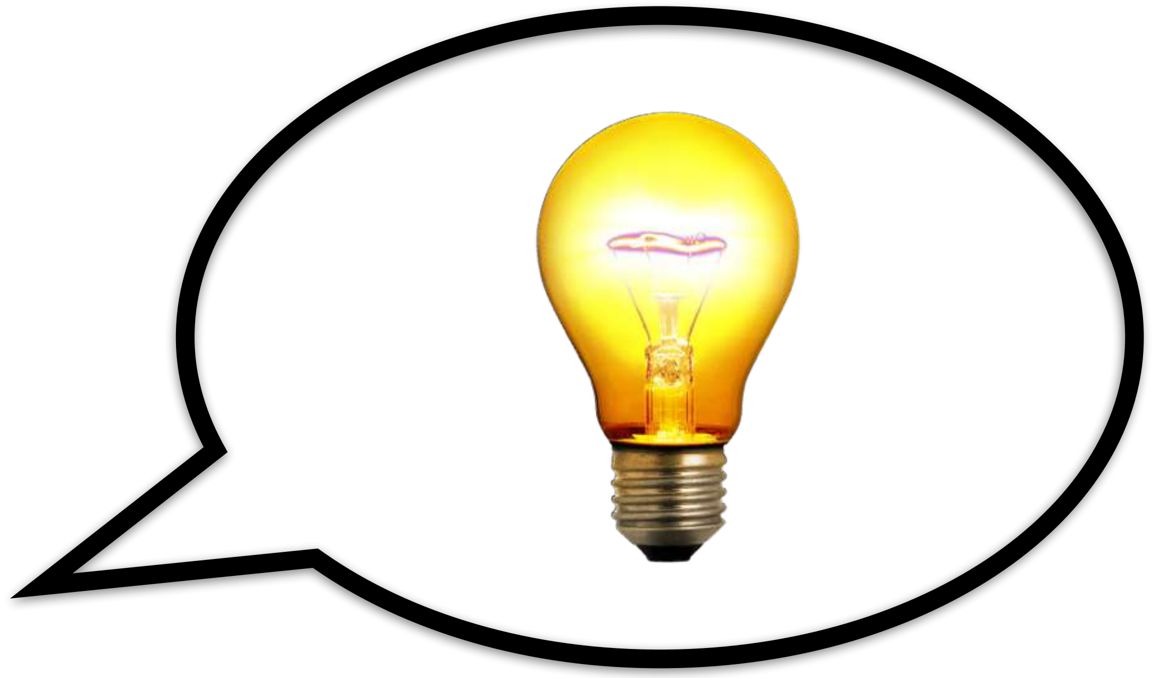
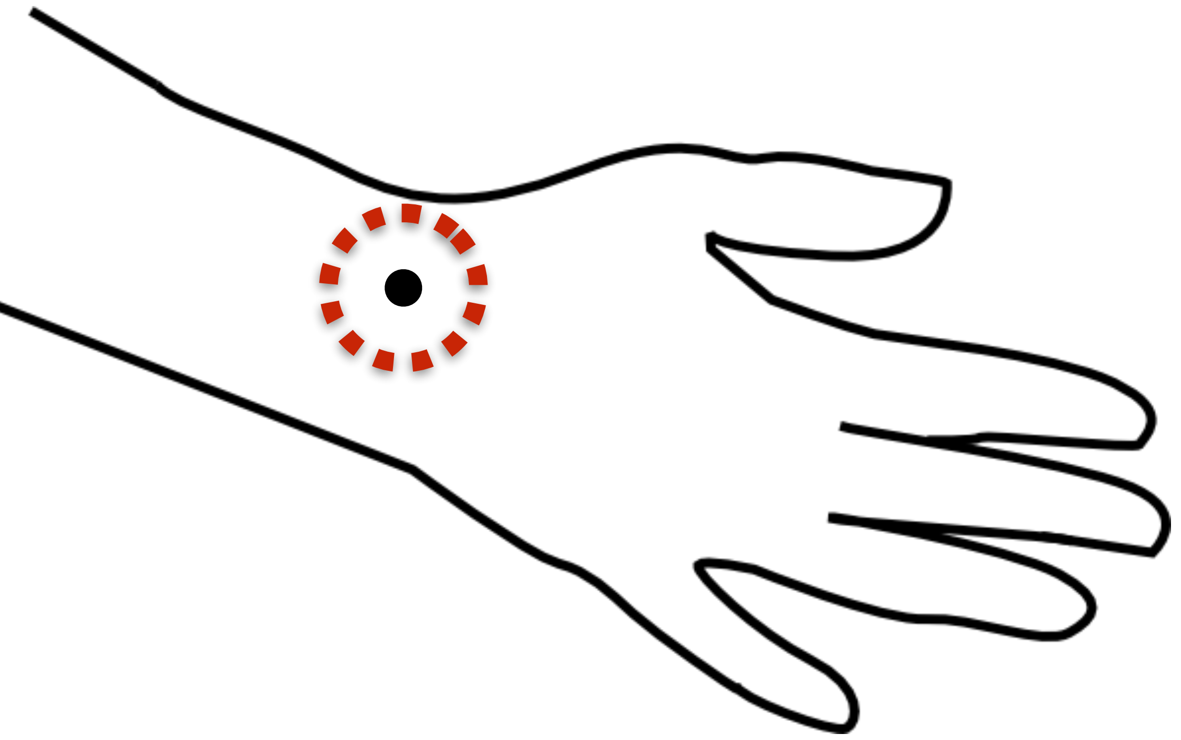
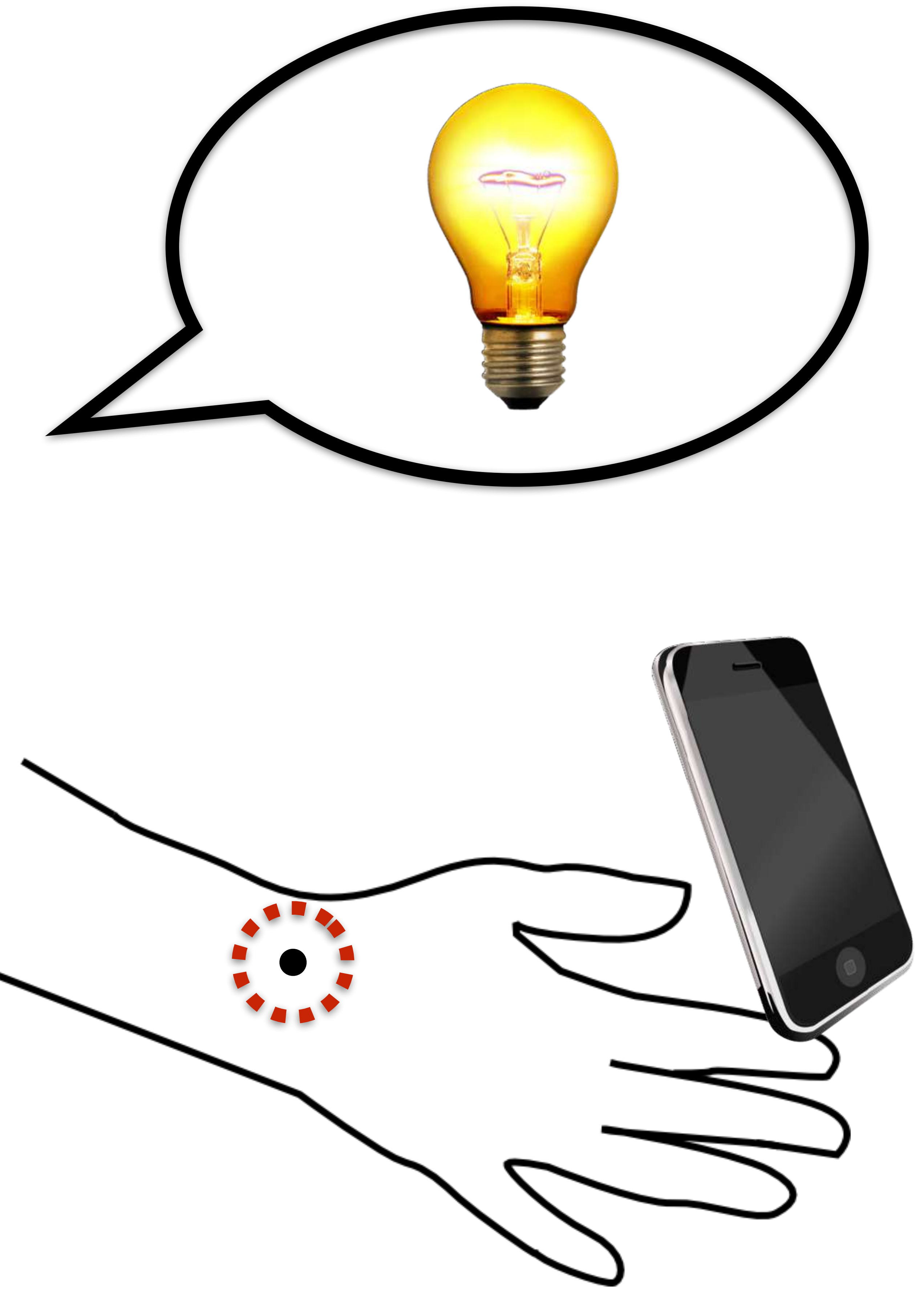


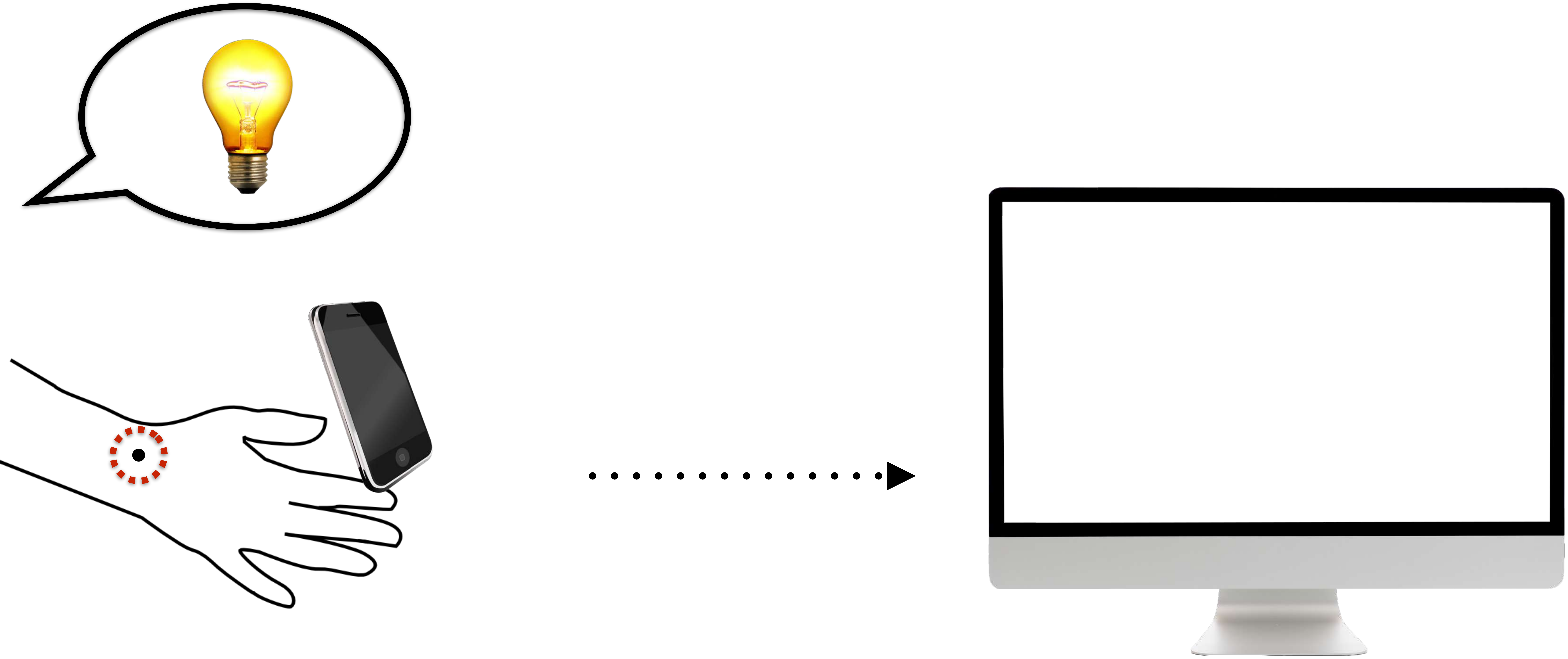


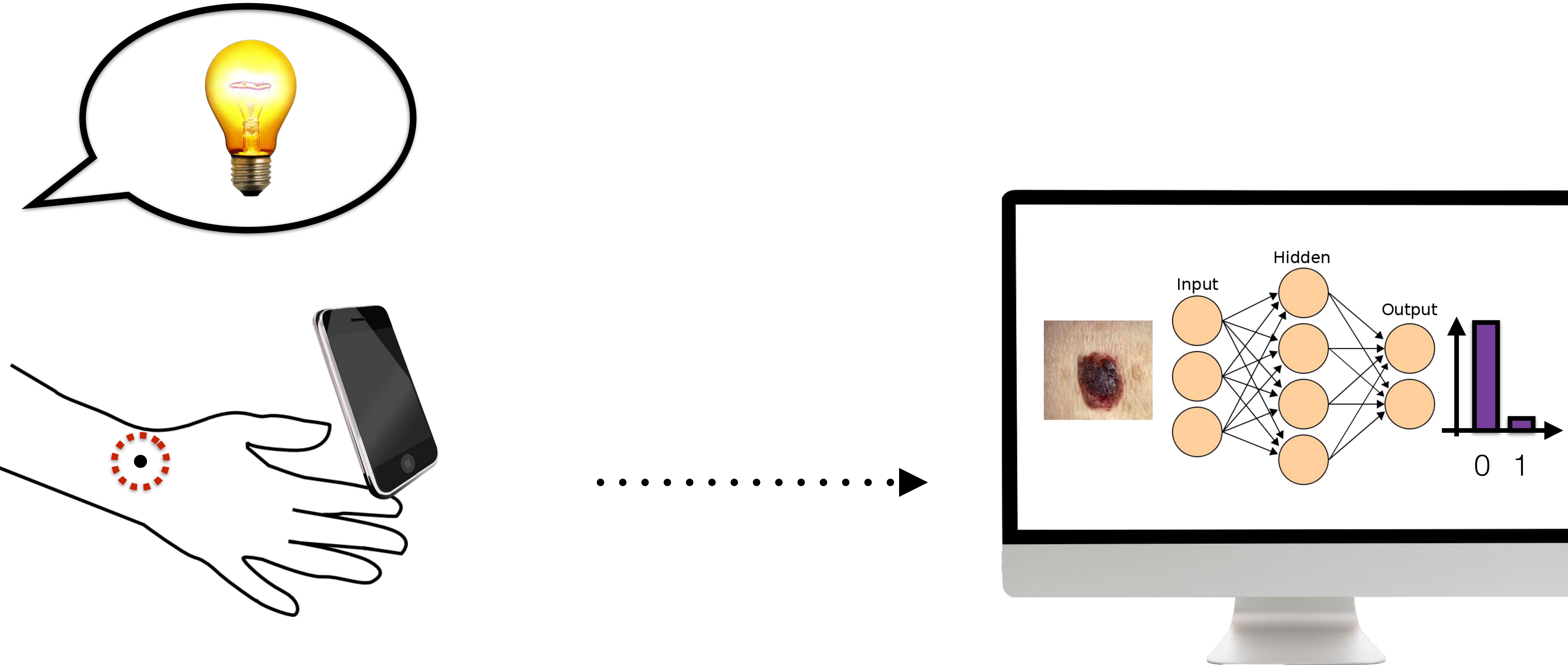

GAME OVER








Input
Hidden
Output
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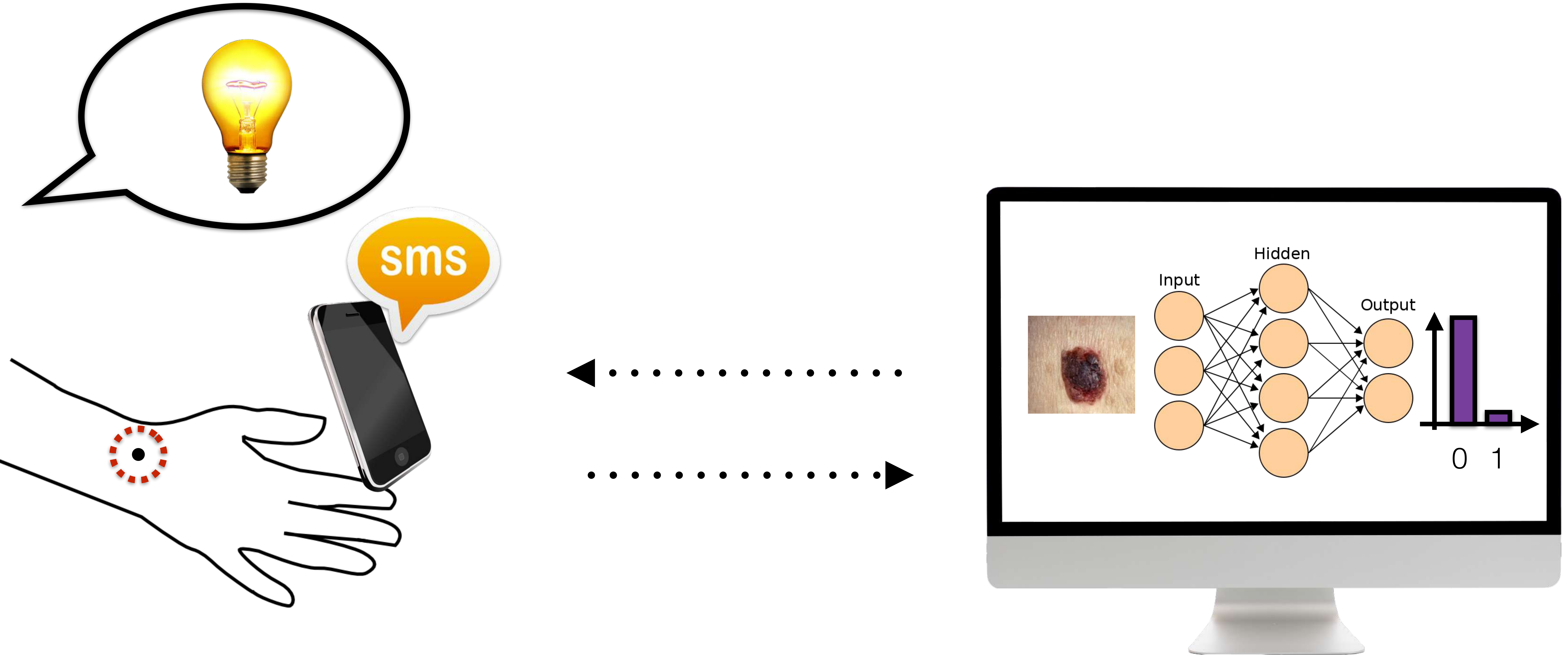
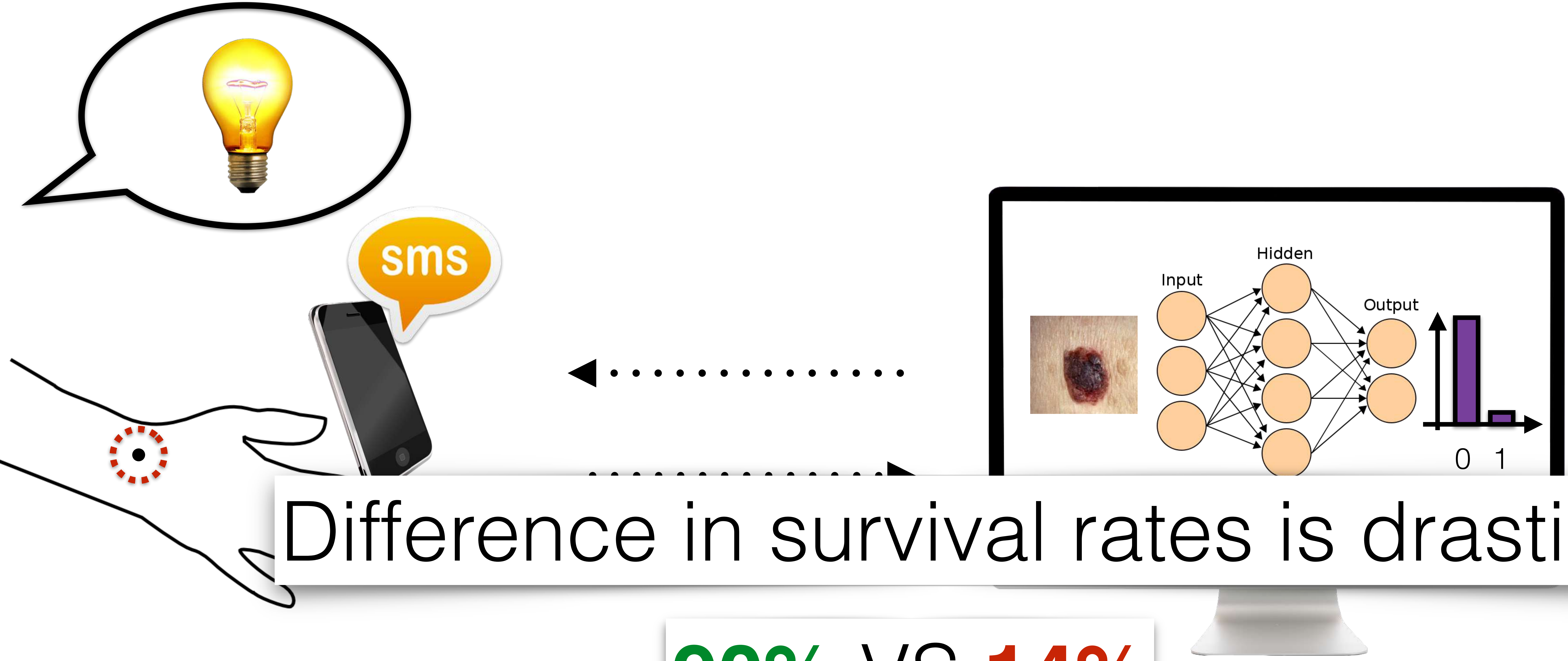
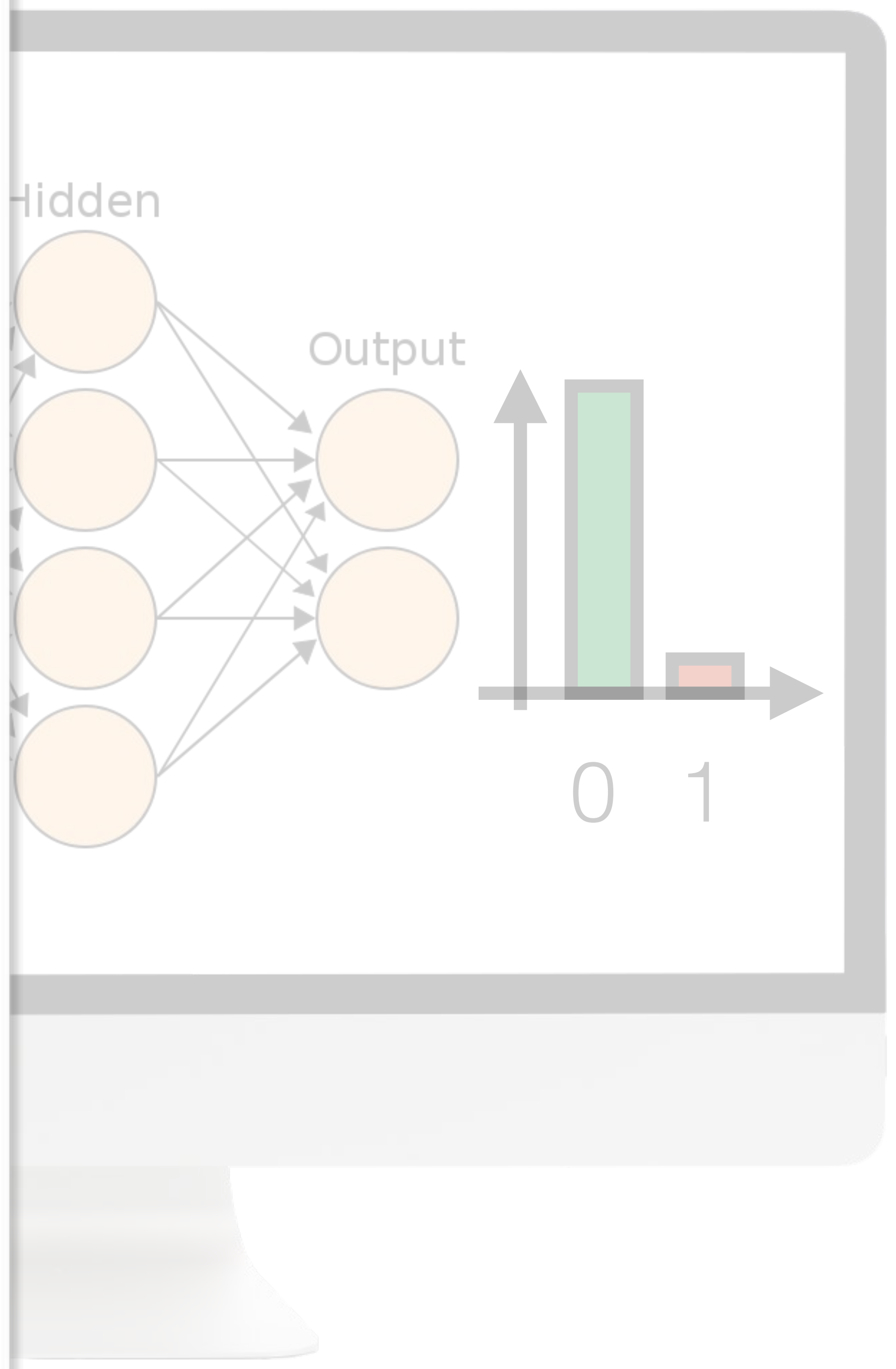
1


sms
Input
Hidden
Output
0
1

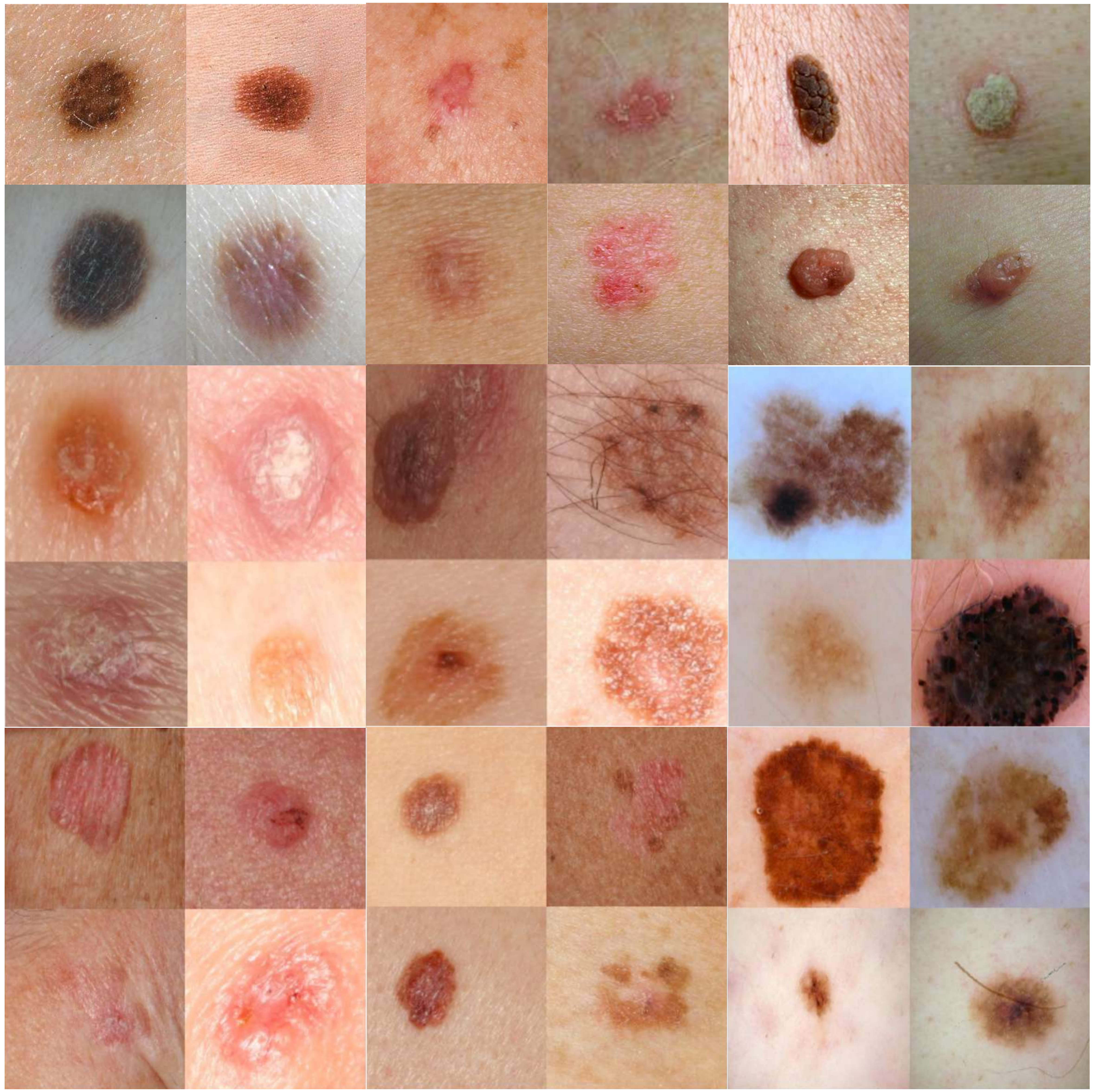


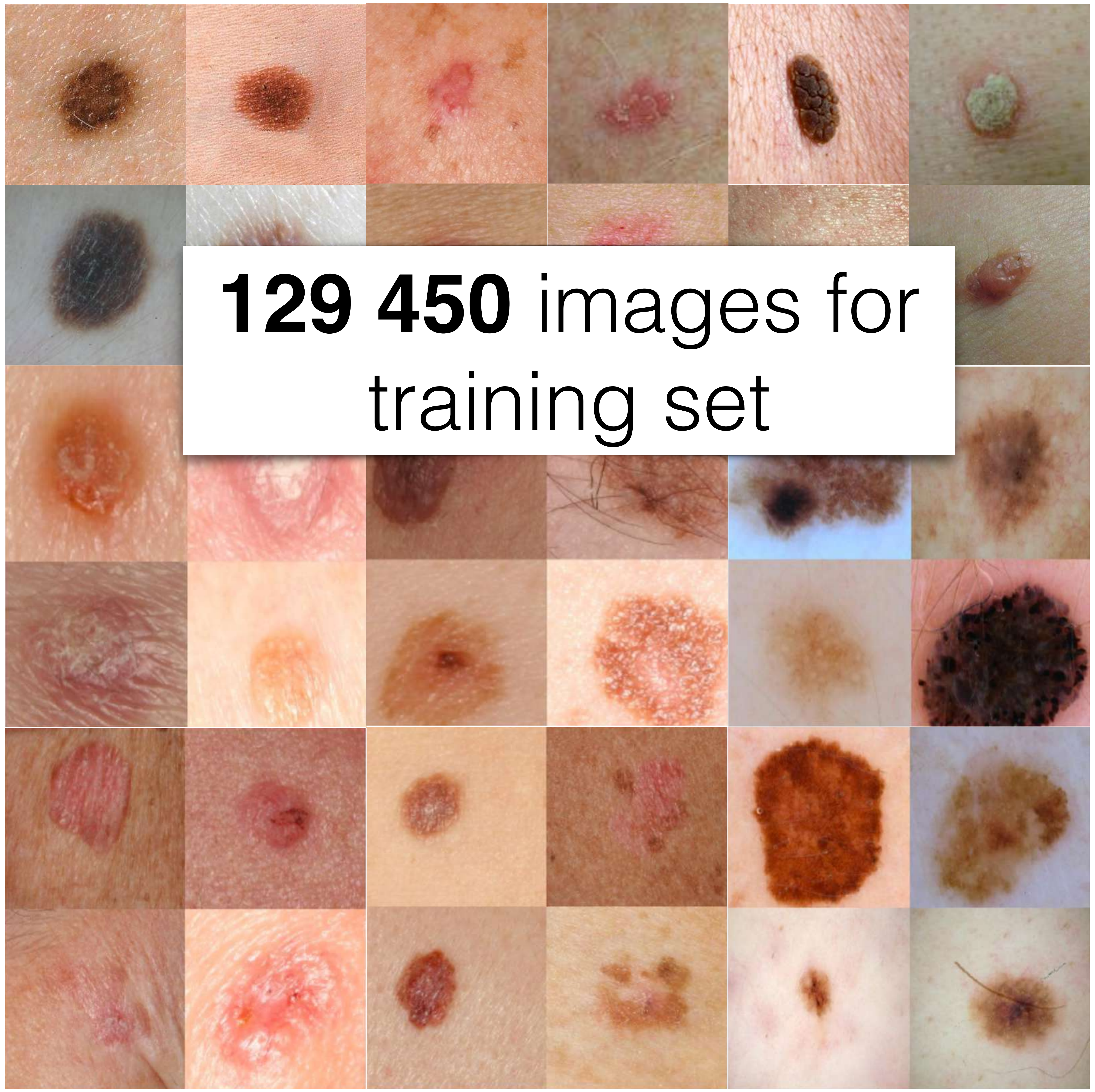
Difference in survival rates is drastic

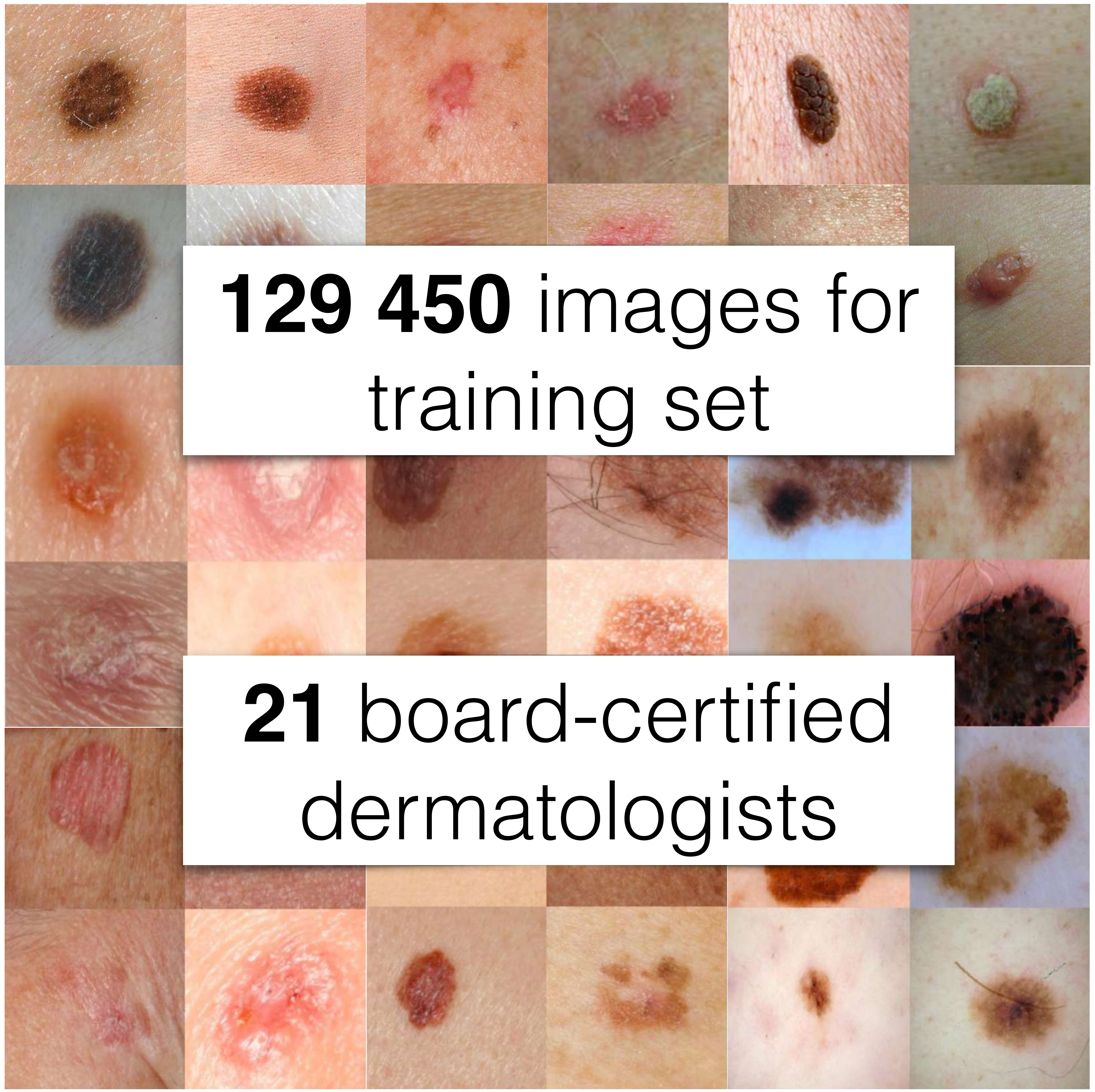
90% VS 14%

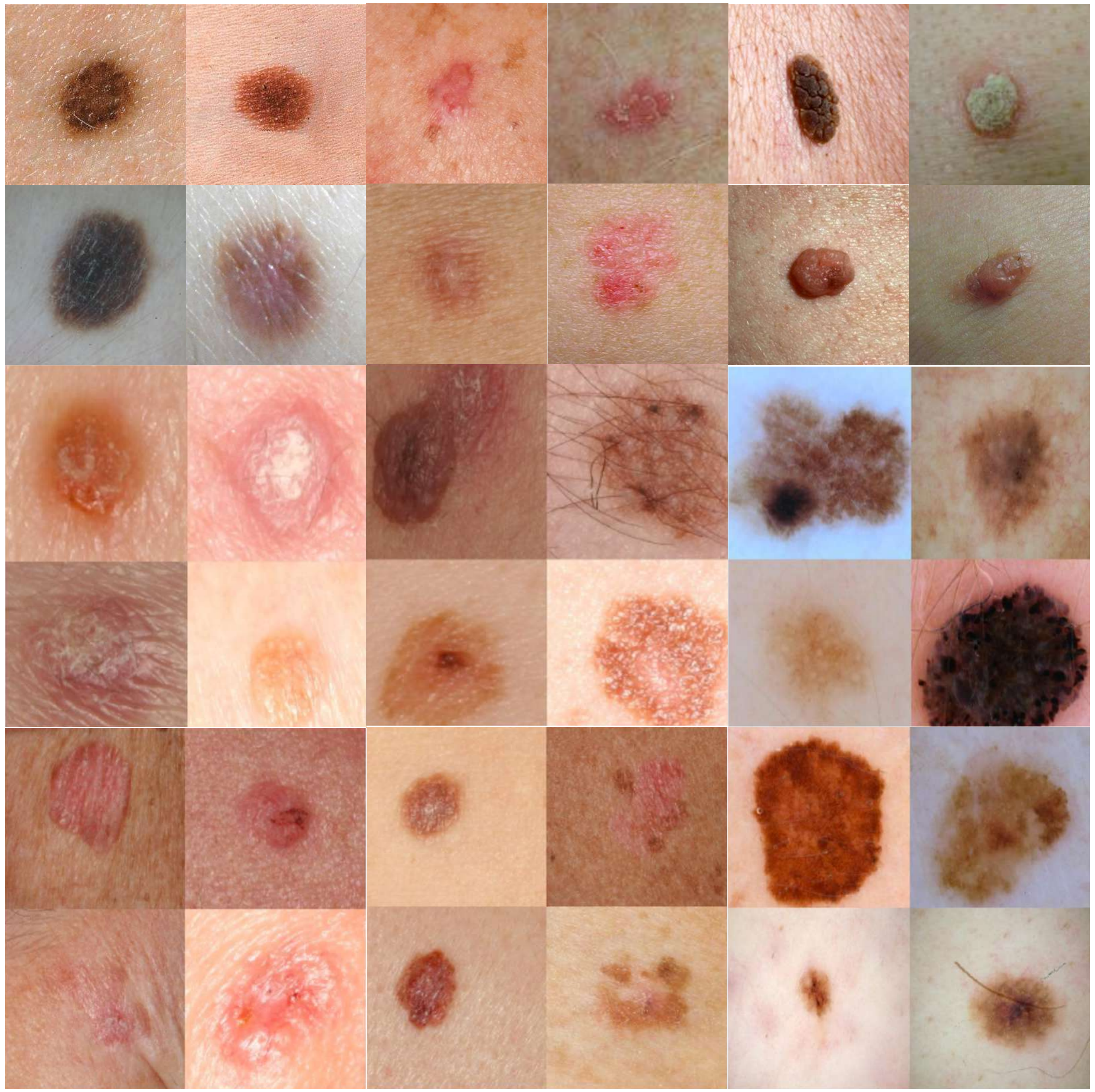


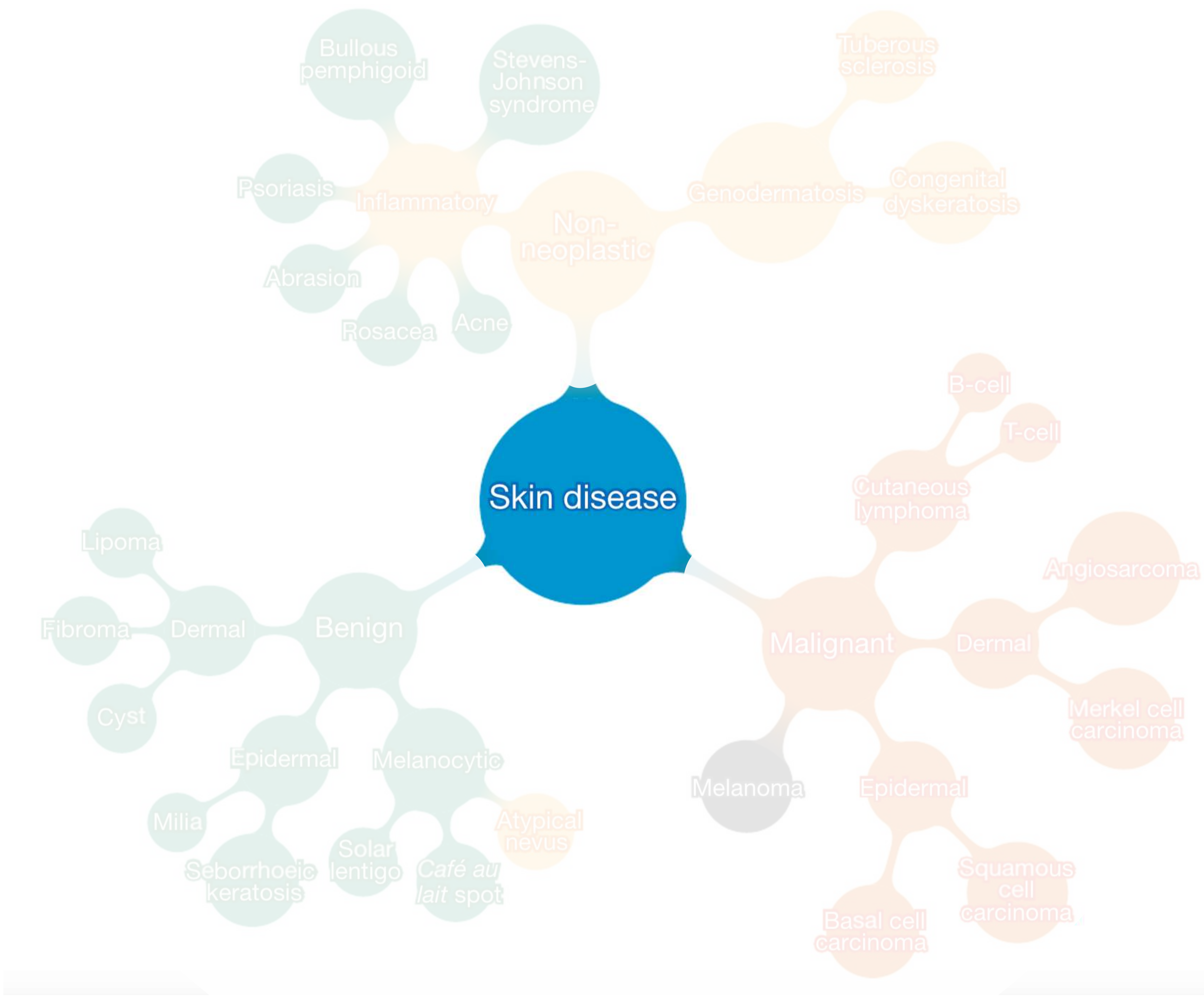
Stanford MEDICINE

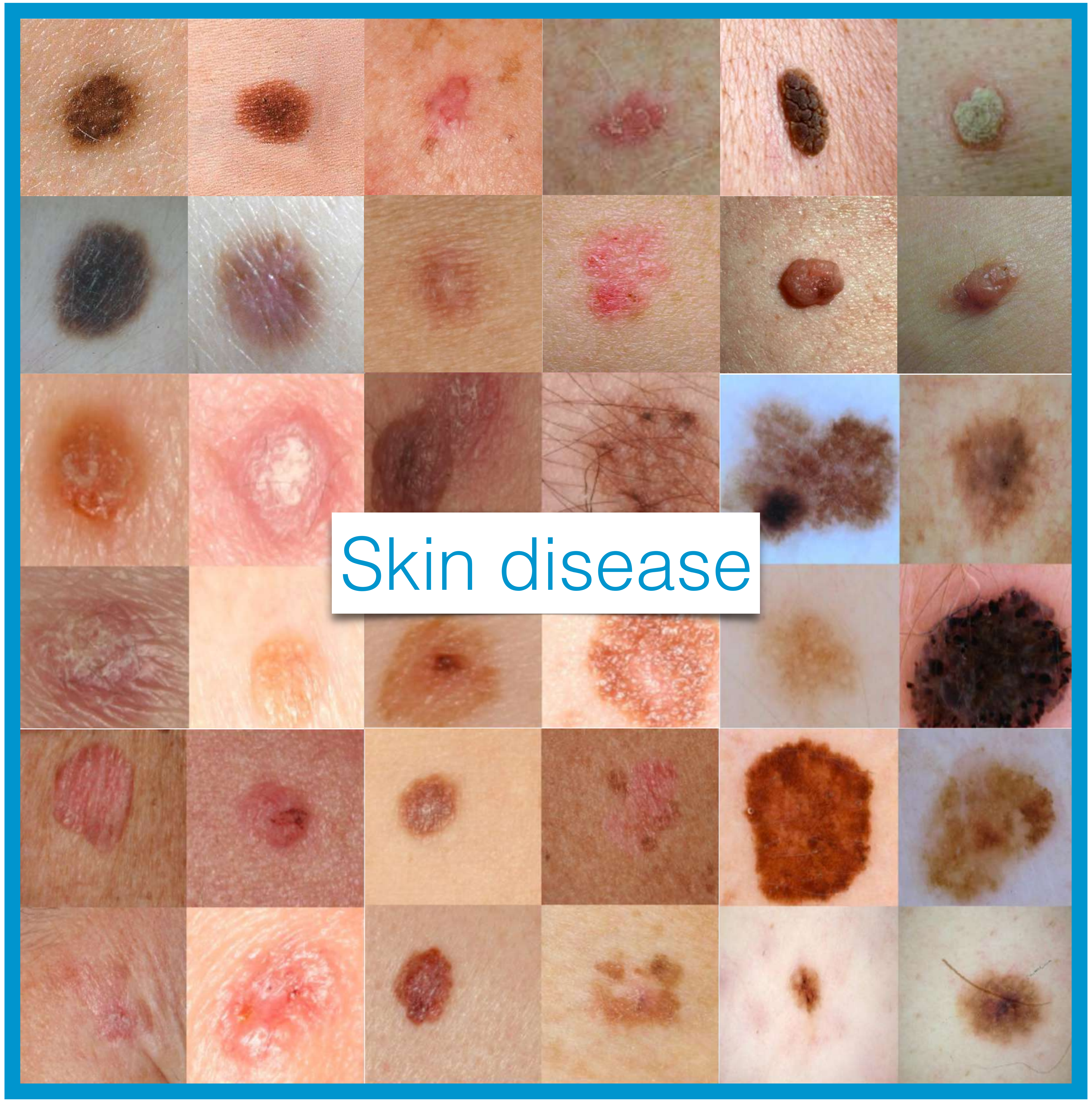


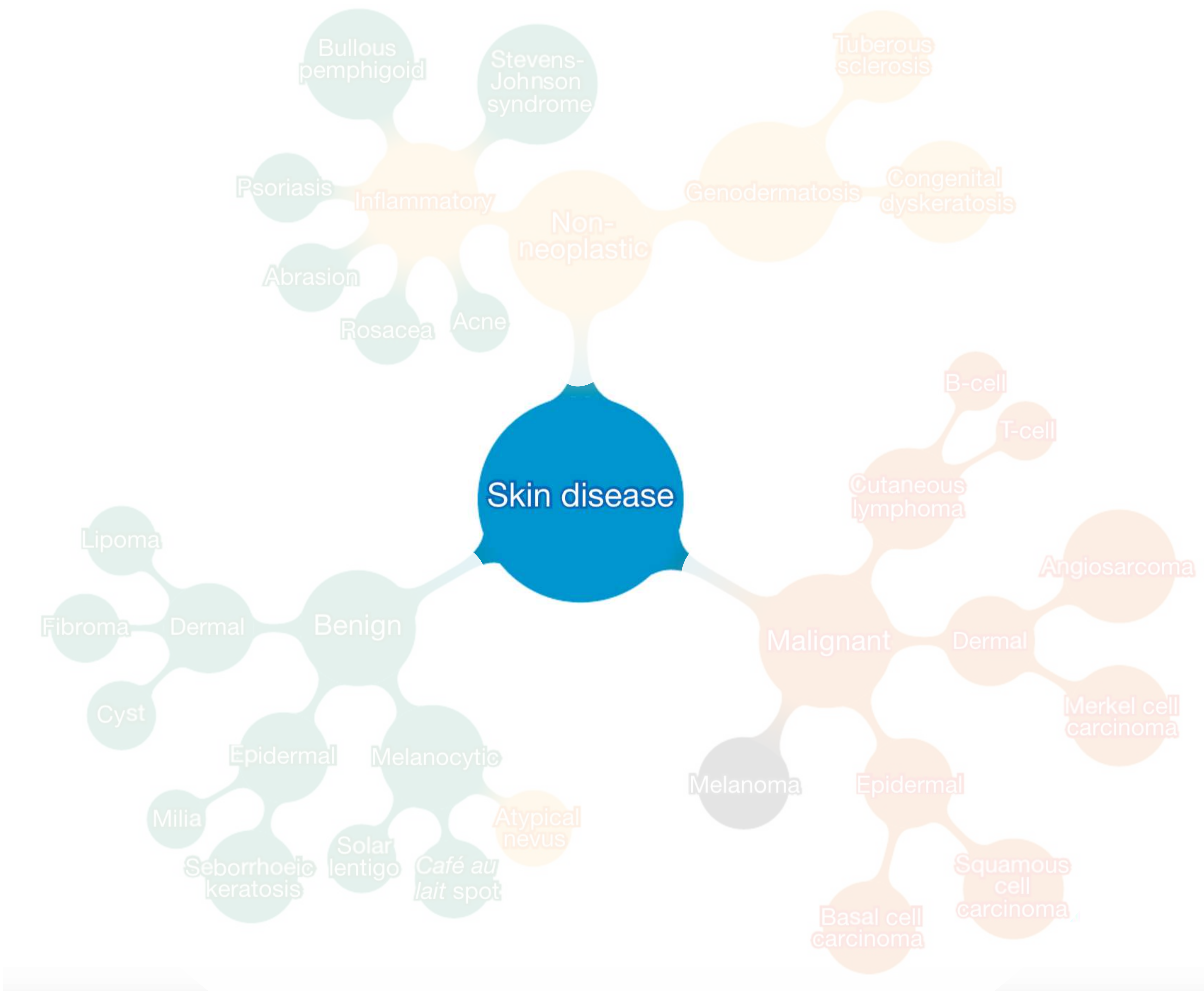

129 450 images for
training set


129 450 images for training set
21 board-certified dermatologists




Skin disease
Non-neoplastic
Inflammatory
Bullous pemphigoid
Stevens-Johnson syndrome
Psoriasis
Abrasion
Rosacea
Acne
Genodermatosis
Tuberous sclerosis
Congenital dyskeratosis
Benign
Dermal
Lipoma
Fibroma
Cyst
Epidermal
Milia
Seborrhoeic keratosis
Melanocytic
Solar lentigo
Café au lait spot
Atypical nevus
Malignant
Cutaneous lymphoma
B-cell
T-cell
Dermal
Angiosarcoma
Merkel cell carcinoma
Melanoma
Epidermal
Squamous cell carcinoma
Basal cell carcinoma


Skin disease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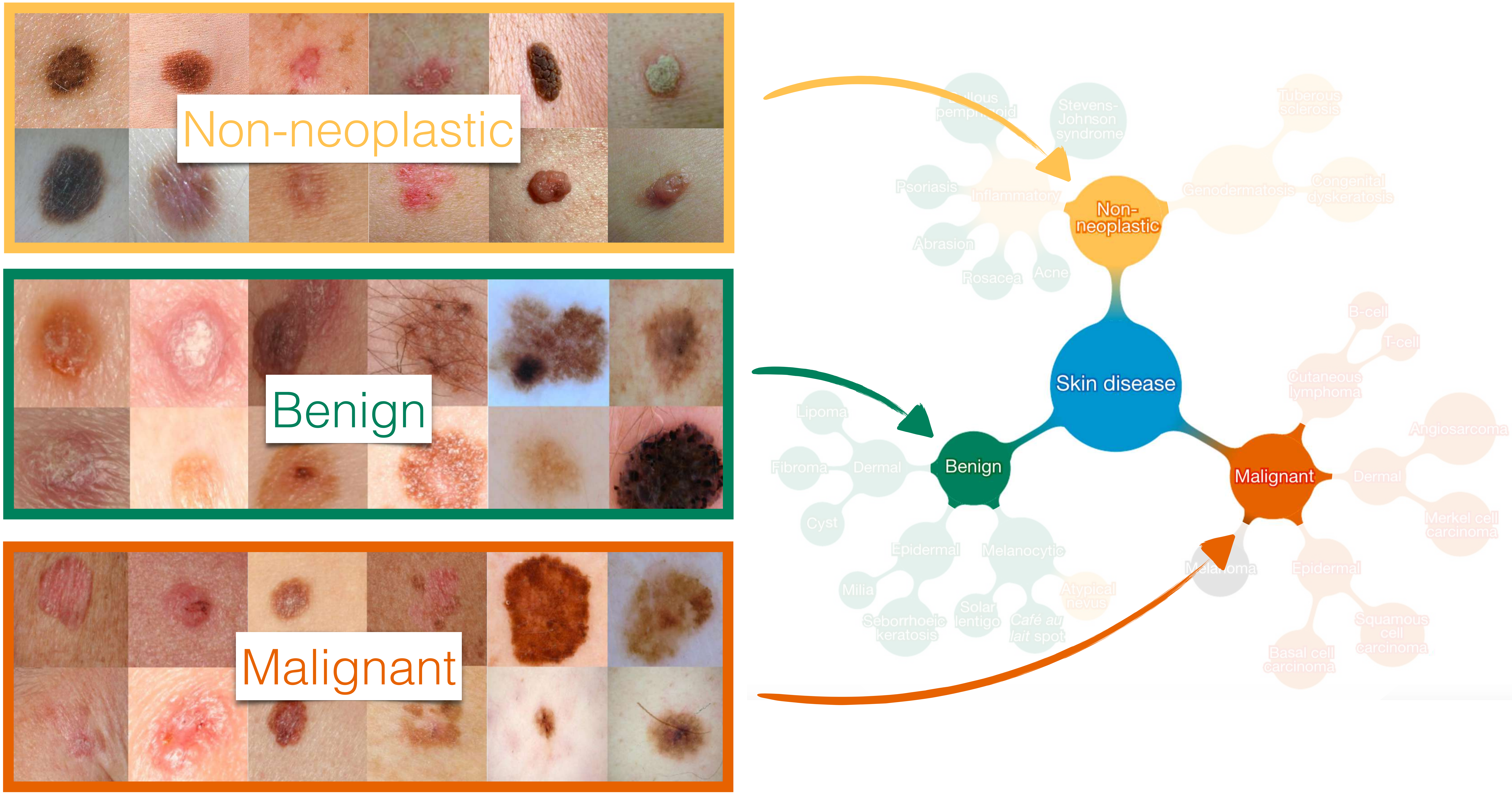

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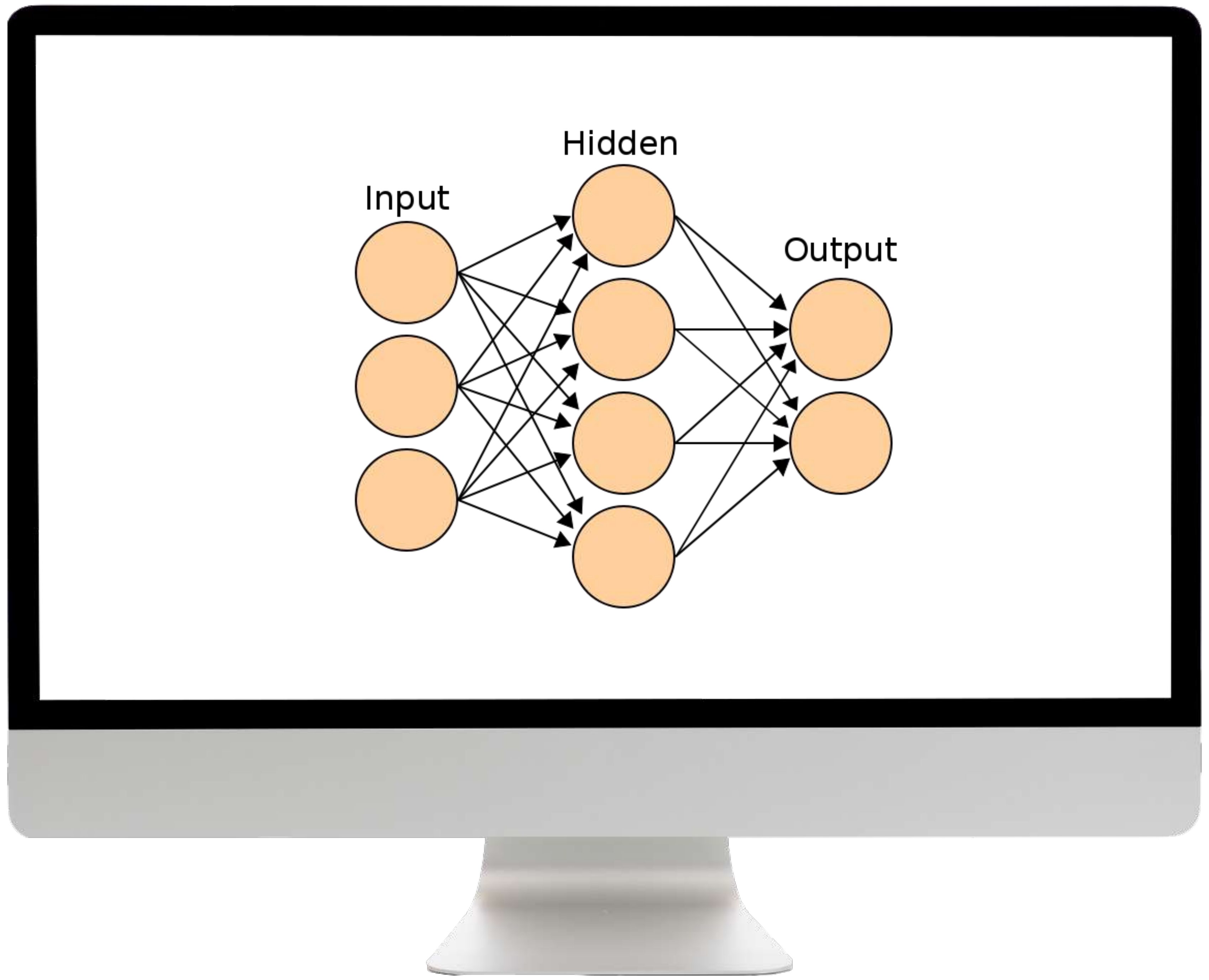
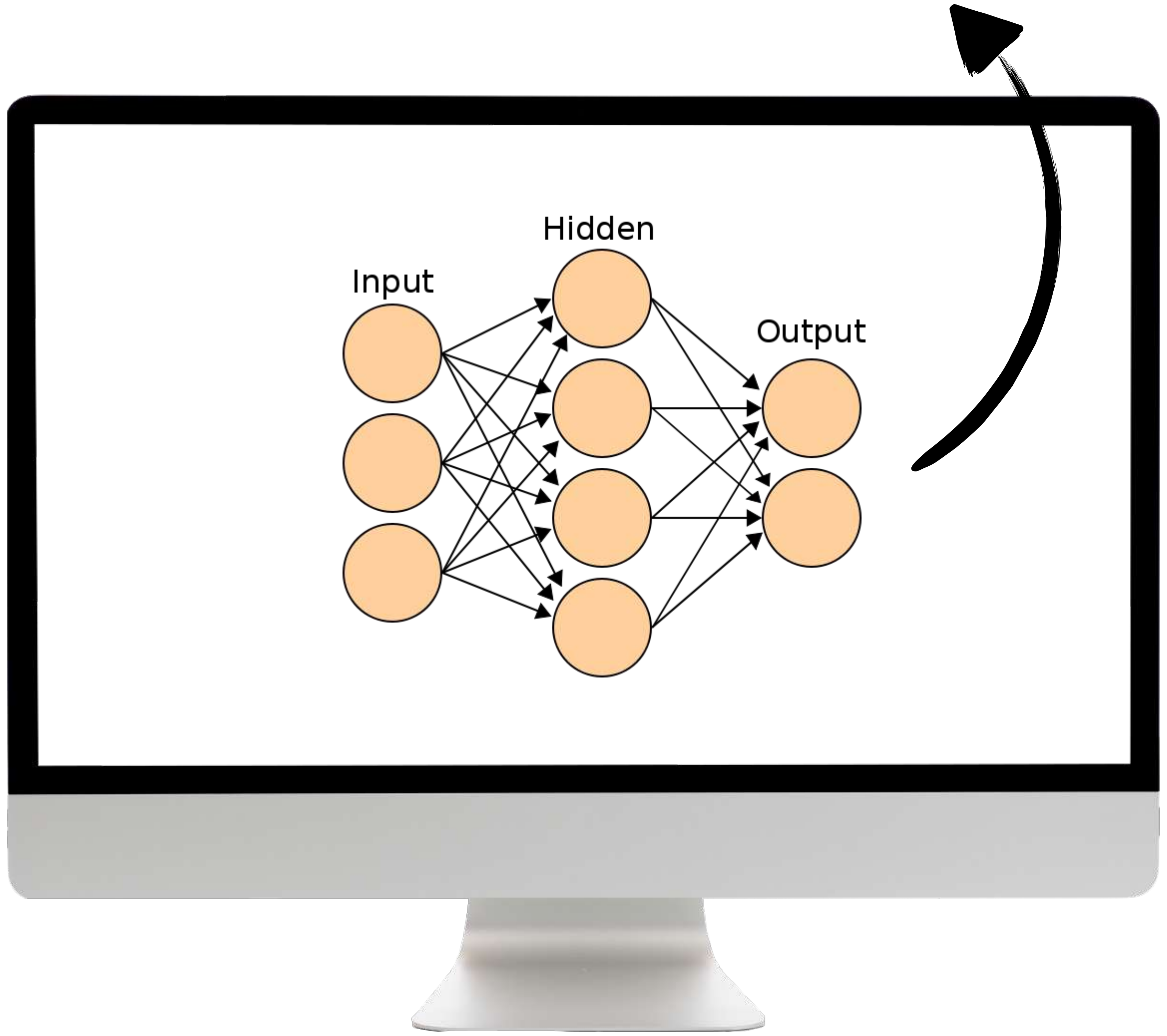
Epidermal
Milia
Atypical nevus
Solar lentigo
Café au lait spot
Seborrheic keratosis
Squamous cell carcinoma
Basal cell carcinoma

Inflammatory
Genodermatosis
Epidermal
Dermal
Melanocytic
Epidermal
Dermal
Melanoma
Lymphoma
Skin disease
Non-neoplastic
Inflammatory
Genodermatosis
Bullous pemphigoid
Stevens-Johnson syndrome
Psoriasis
Abrasion
Rosacea
Acne
Tuberous sclerosis
Congenital dyskeratosis
Benign
Dermal
Epidermal
Melanocytic
Lipoma
Fibroma
Cyst
Milia
Seborrhoeic keratosis
Solar lentigo
Café au lait spot
Atypical nevus
Malignant
Cutaneous lymphoma
B-cell
T-cell
Dermal
Angiosarcoma
Merkel cell carcinoma
Melanoma
Epidermal
Squamous cell carcinoma
Basal cell carcinoma

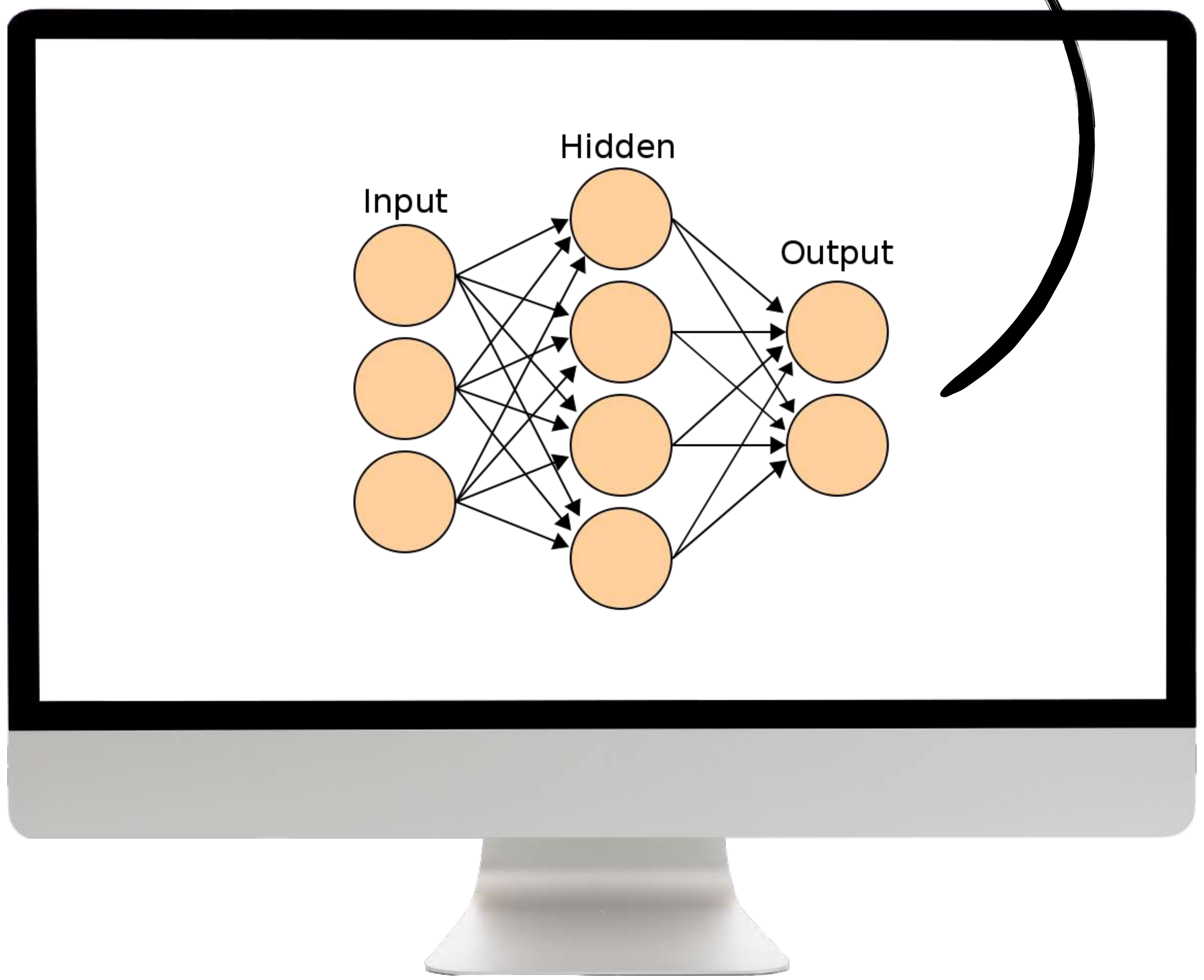

Inflammatory
Genodermatosis
Epidermal
Dermal
Melanocytic
Epidermal
Dermal
Melanoma
Lymphoma
Skin disease
Non-neoplastic
Inflammatory
Bullous pemphigoid
Stevens-Johnson syndrome
Psoriasis
Abrasion
Rosacea
Acne
Genodermatosis
Tuberous sclerosis
Congenital dyskeratosis
Benign
Dermal
Lipoma
Fibroma
Cyst
Epidermal
Milia
Seborrhoeic keratosis
Melanocytic
Solar lentigo
Café au lait spot
Atypical nevus
Malignant
Cutaneous lymphoma
B-cell
T-cell
Dermal
Angiosarcoma
Merkel cell carcinoma
Melanoma
Epidermal
Squamous cell carcinoma
Basal cell carcinoma

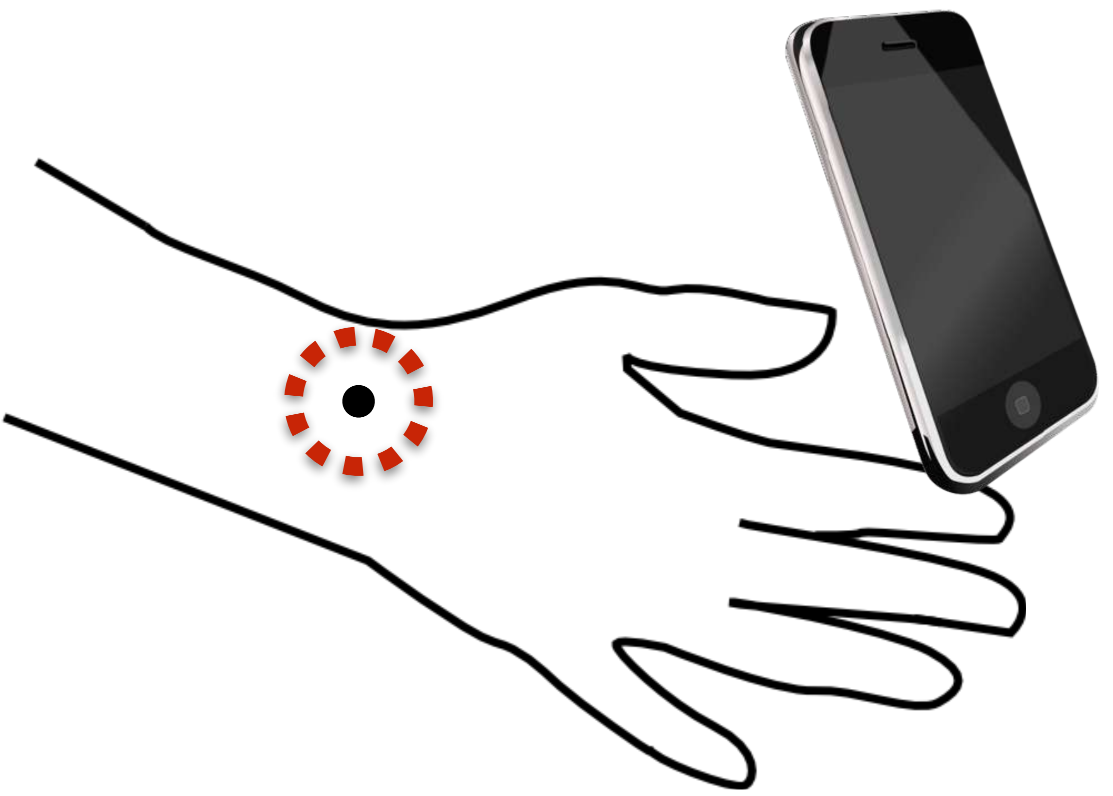

Hidden
Input
Output

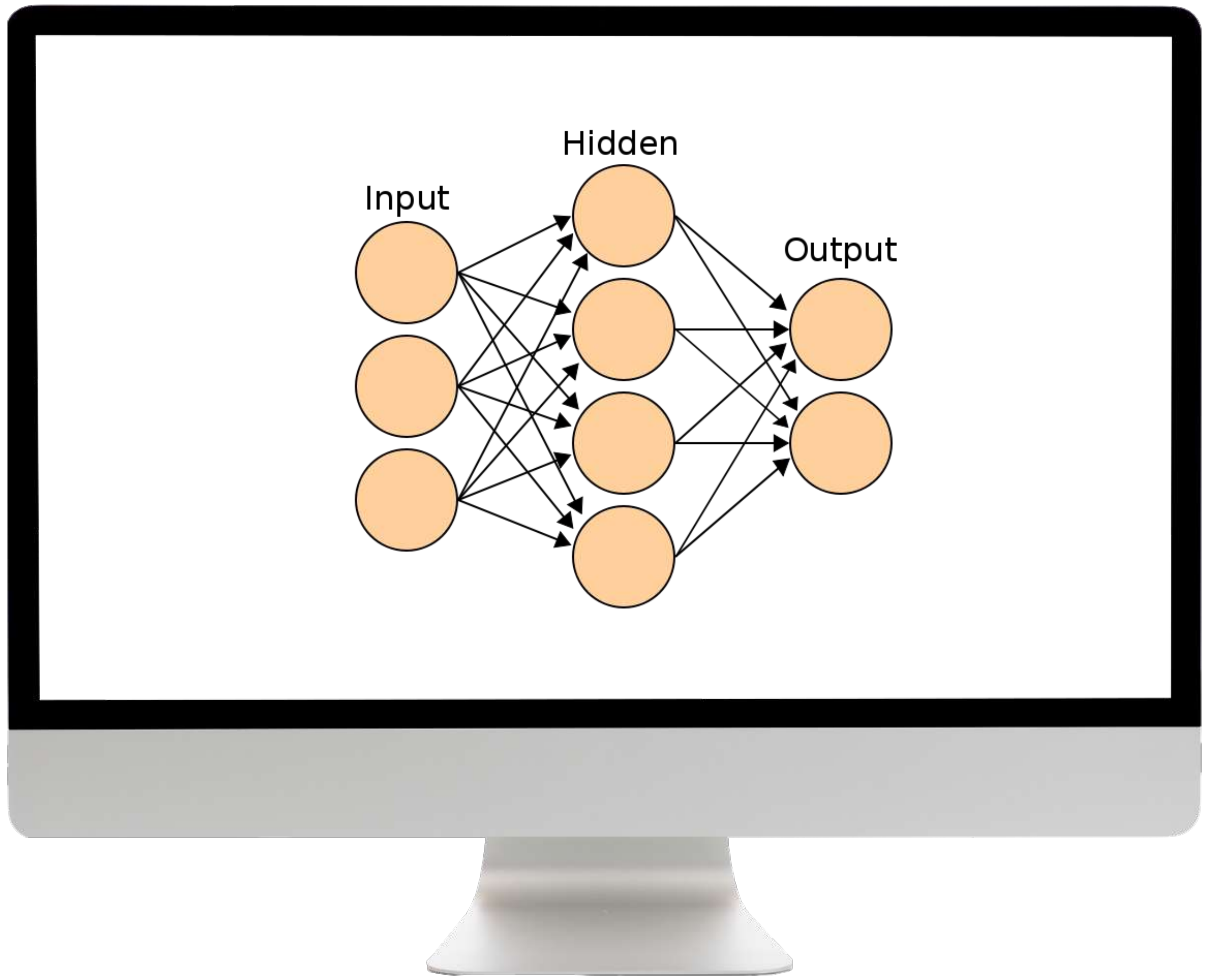
Google Inception v3



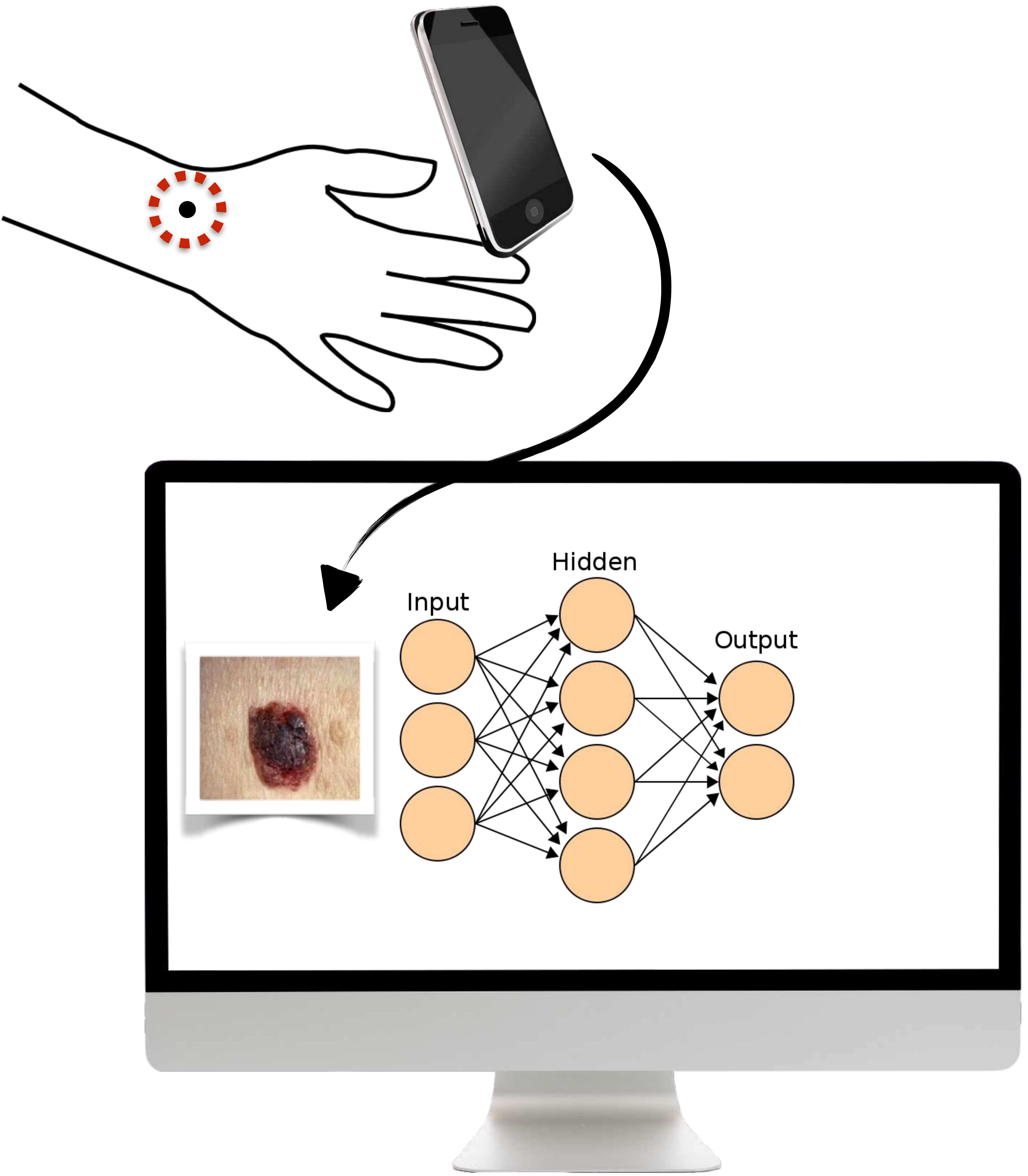
Google Inception v3

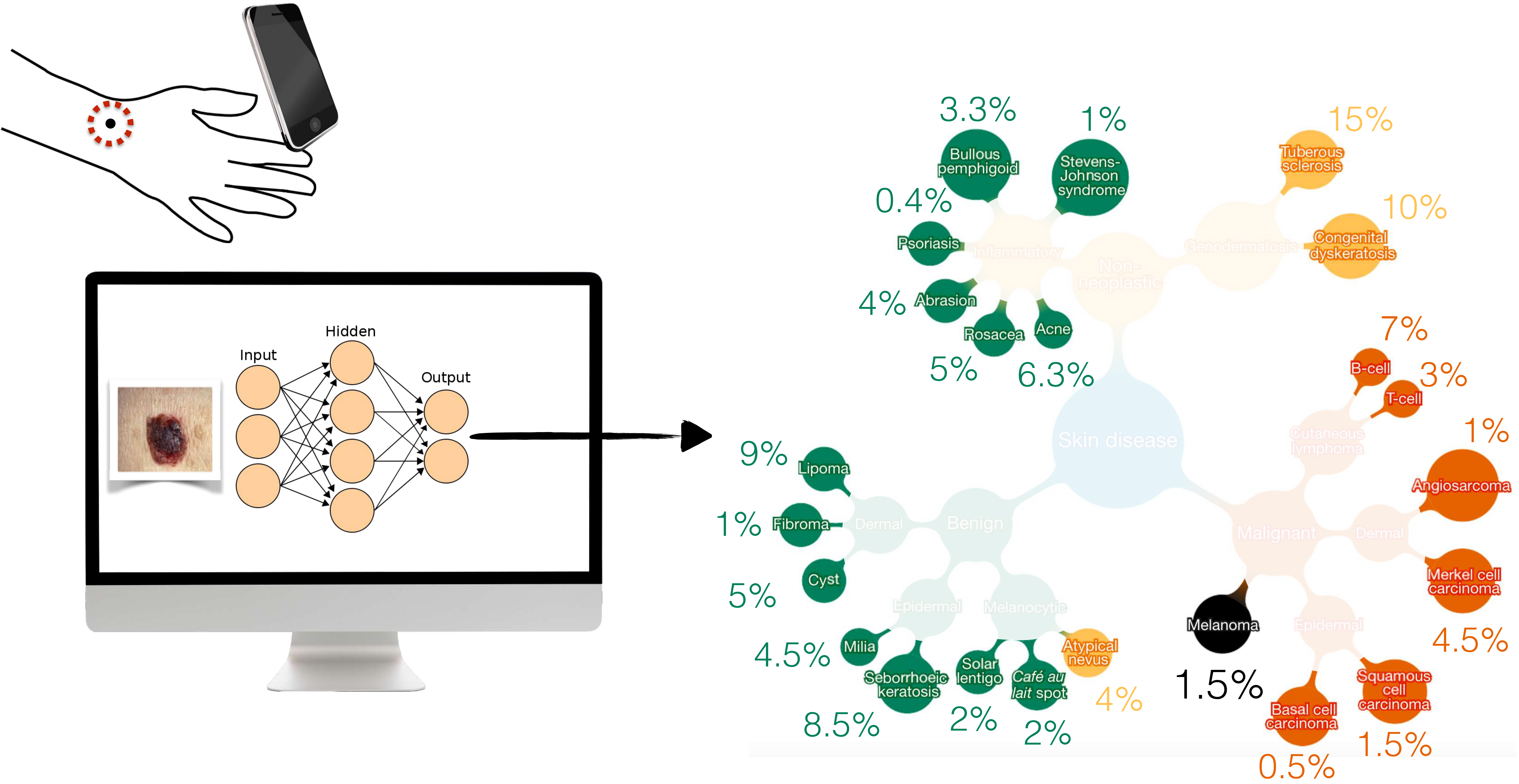




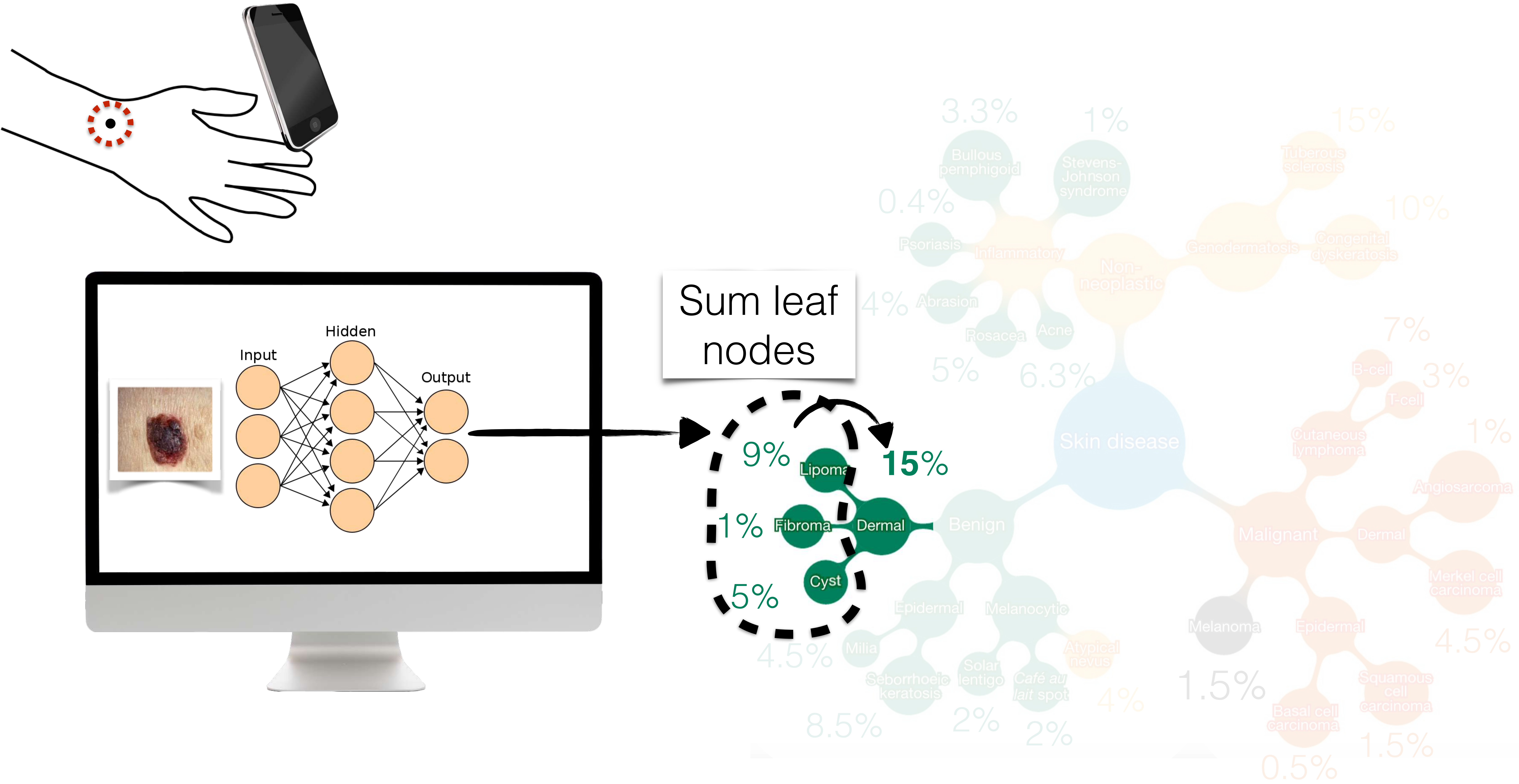


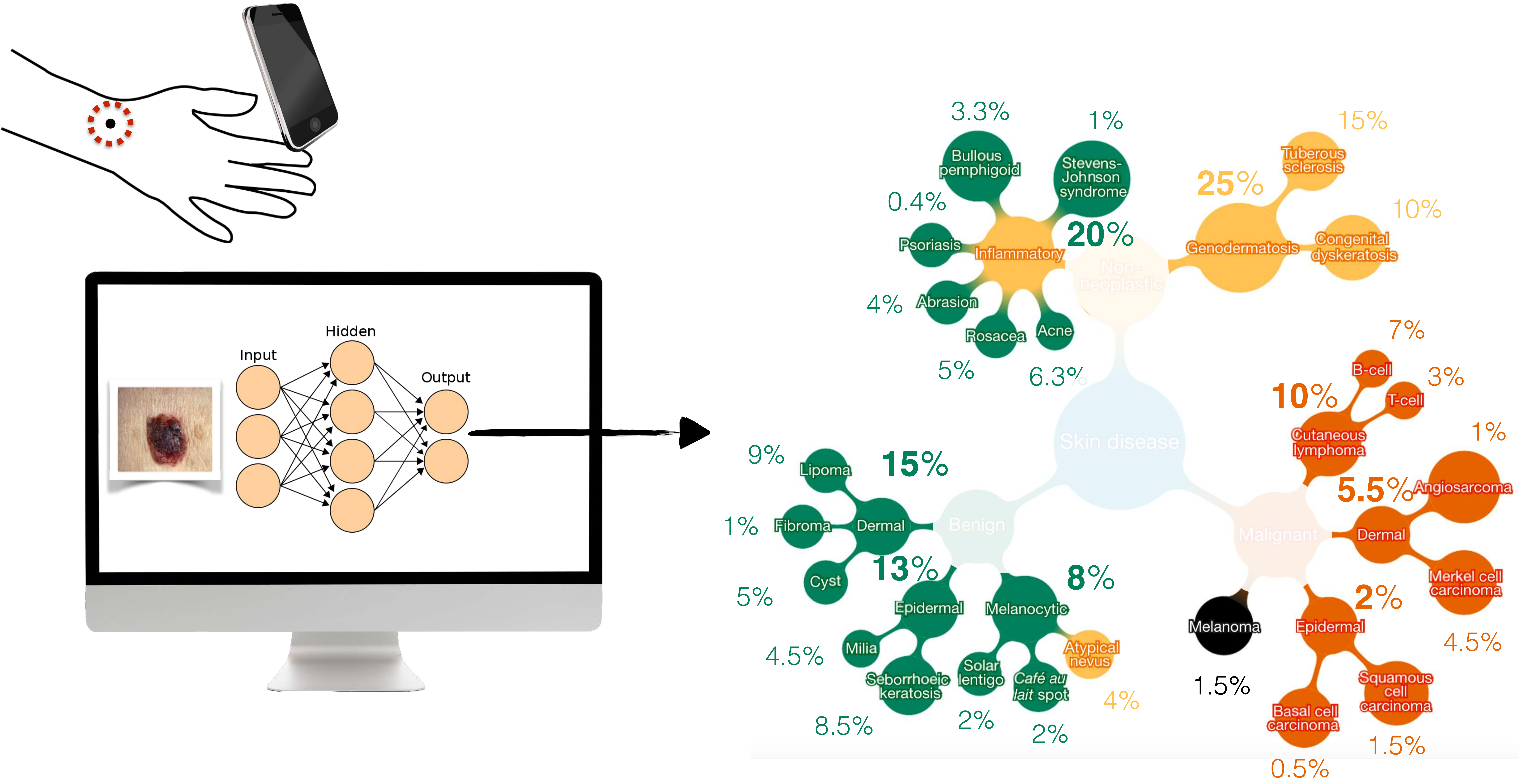
Hidden
Input
Output


Hidden
Input
Output

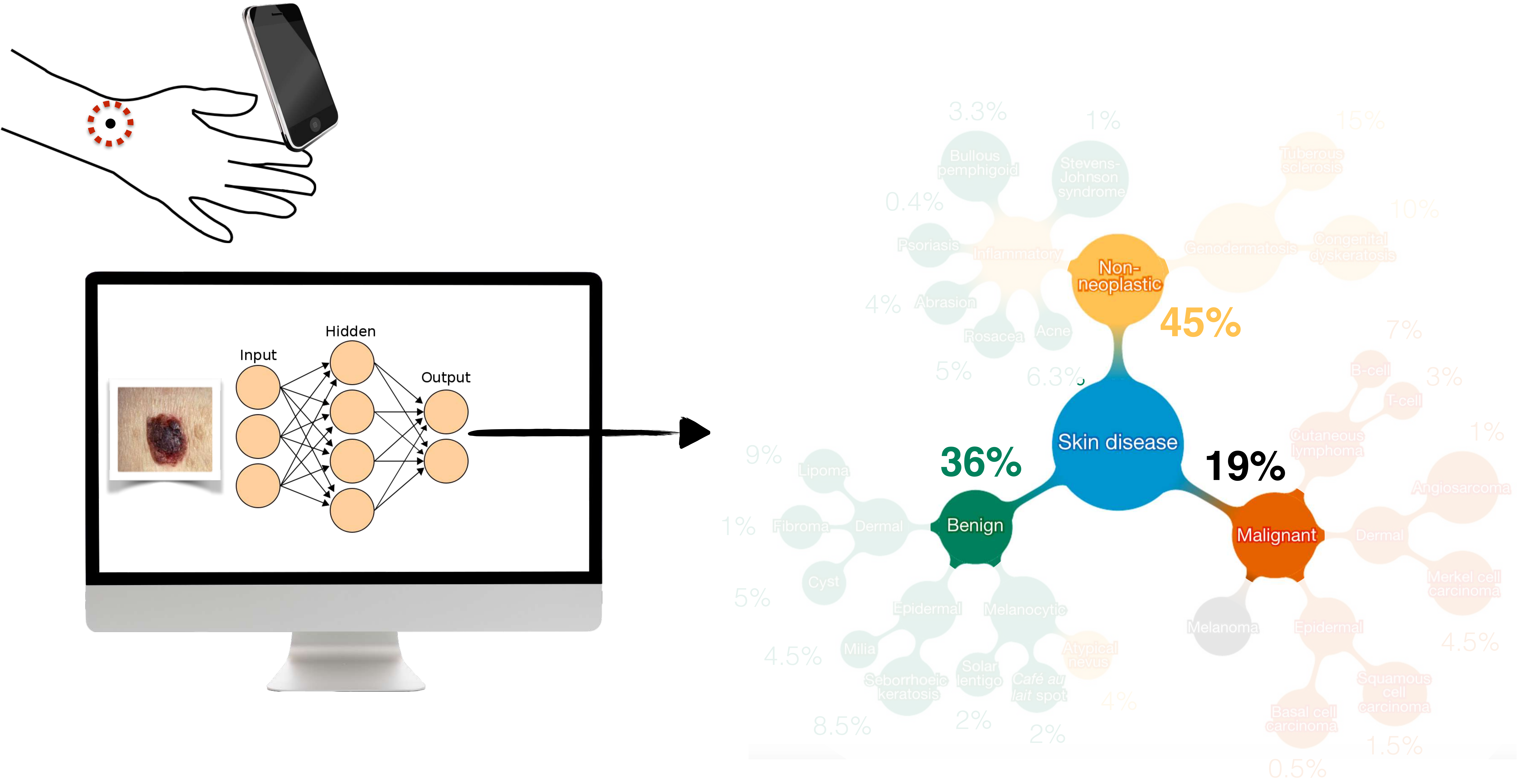


Input
Hidden
Output
Skin disease
Non-neoplastic
Inflammatory
Genodermatosis
Bullous pemphigoid
3.3%
Stevens-Johnson syndrome
1%
Psoriasis
0.4%
Abrasion
4%
Rosacea
5%
Acne
6.3%
Tuberous sclerosis
15%
Congenital dyskeratosis
10%
Benign
Dermal
Epidermal
Melanocytic
Lipoma
9%
Fibroma
1%
Cyst
5%
Milia
4.5%
Seborrhoeic keratosis
8.5%
Solar lentigo
2%
Café au lait spot
2%
Atypical nevus
4%
Malignant
Cutaneous lymphoma
Dermal
Epidermal
B-cell
7%
T-cell
3%
Angiosarcoma
1%
Merkel cell carcinoma
4.5%
Melanoma
1.5%
Basal cell carcinoma
0.5%
Squamous cell carcinoma
1.5%

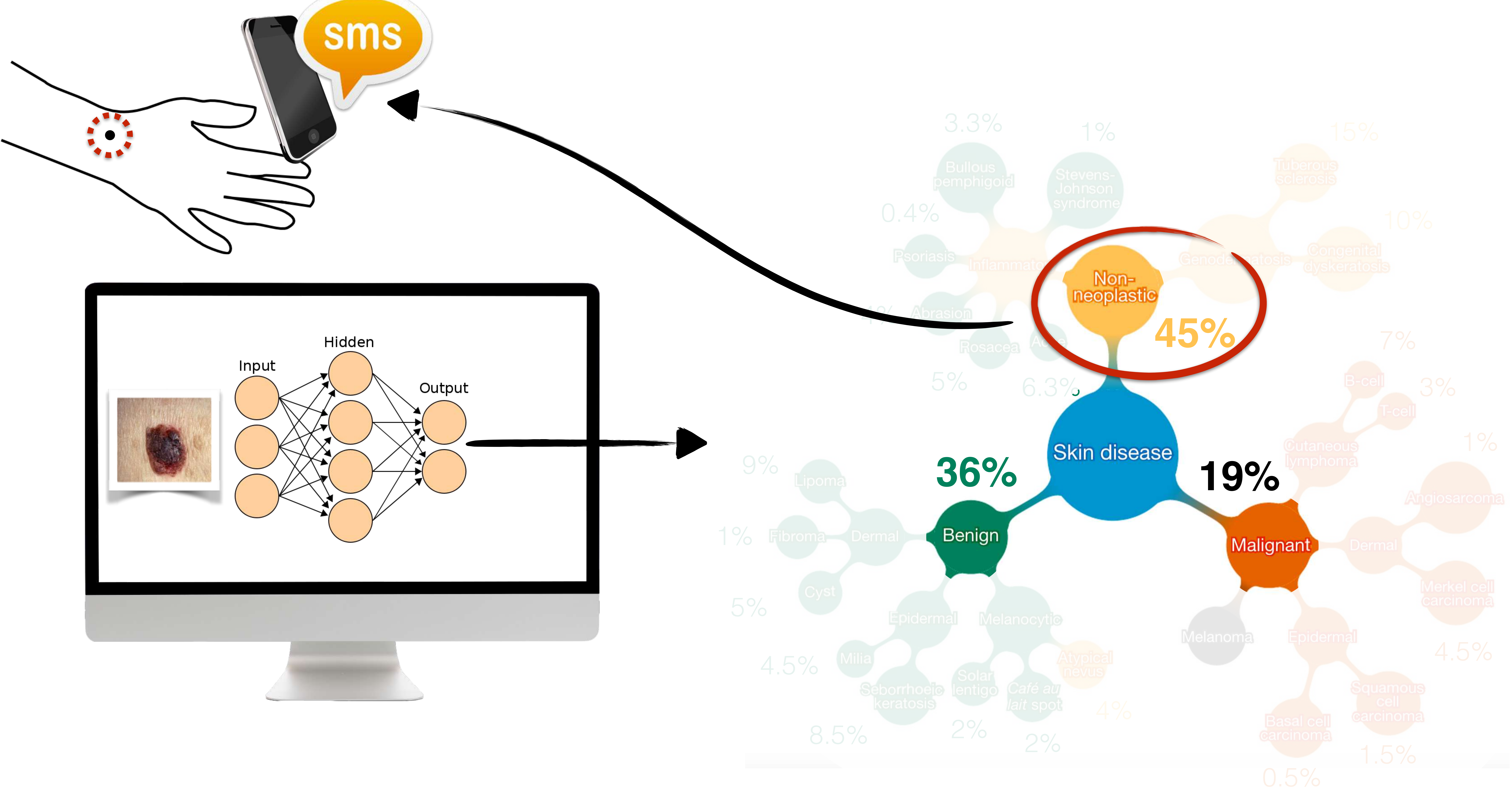

Input
Hidden
Output
Sum leaf nodes
9%
1%
5%
15%
Lipoma
Fibroma
Dermal
Cyst
Benign
Skin disease
Malignant
Non-neoplastic
Inflammatory
Genodermatosis
Bullous pemphigoid
Stevens-Johnson syndrome
Tuberous sclerosis
Congenital dyskeratosis
Psoriasis
Abrasion
Rosacea
Acne
B-cell
T-cell
Cutaneous lymphoma
Angiosarcoma
Dermal
Merkel cell carcinoma
Melanoma
Epidermal
Squamous cell carcinoma
Basal cell carcinoma
Epidermal
Melanocytic
Milia
Seborrhoeic keratosis
Solar lentigo
Café au lait spot
Atypical nevus
3.3%
1%
15%
0.4%
10%
4%
5%
6.3%
7%
3%
1%
4.5%
4.5%
8.5%
2%
2%
4%
1.5%
1.5%
0.5%



Hidden
Input
Output
Skin disease
Non-neoplastic
20%
Inflammatory
Bullous pemphigoid
3.3%
Stevens-Johnson syndrome
1%
Psoriasis
0.4%
Abrasion
4%
Rosacea
5%
Acne
6.3%
25%
Genodermatosis
Tuberous sclerosis
15%
Congenital dyskeratosis
10%
Benign
15%
Dermal
Lipoma
9%
Fibroma
1%
Cyst
5%
13%
Epidermal
Milia
4.5%
Seborrhoeic keratosis
8.5%
8%
Melanocytic
Solar lentigo
2%
Café au lait spot
2%
Atypical nevus
4%
Malignant
10%
Cutaneous lymphoma
B-cell
7%
T-cell
3%
5.5%
Dermal
Angiosarcoma
1%
Merkel cell carcinoma
4.5%
Melanoma
1.5%
2%
Epidermal
Basal cell carcinoma
0.5%
Squamous cell carcinoma
1.5%



Input
Hidden
Output
Non-neoplastic
45%
Skin disease
36%
19%
Benign
Malignant
Inflammatory
Genodermatosis
Bullous pemphigoid
Stevens-Johnson syndrome
Psoriasis
Abrasion
Rosacea
Acne
Tuberous sclerosis
Congenital dyskeratosis
B-cell
T-cell
Cutaneous lymphoma
Angiosarcoma
Dermal
Merkel cell carcinoma
Melanoma
Epidermal
Squamous cell carcinoma
Basal cell carcinoma
Lipoma
Fibroma
Dermal
Cyst
Epidermal
Melanocytic
Milia
Seborrhoeic keratosis
Solar lentigo
Café au lait spot
Atypical nevus


sms
Input
Hidden
Output
Non-neoplastic
45%
Skin disease
36%
Benign
19%
Malignant
Bullous pemphigoid
Stevens-Johnson syndrome
Psoriasis
Abrasion
Rosacea
Tuberous sclerosis
Congenital dyskeratosis
B-cell
T-cell
Cutaneous lymphoma
Angiosarcoma
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Merkel cell carcinoma
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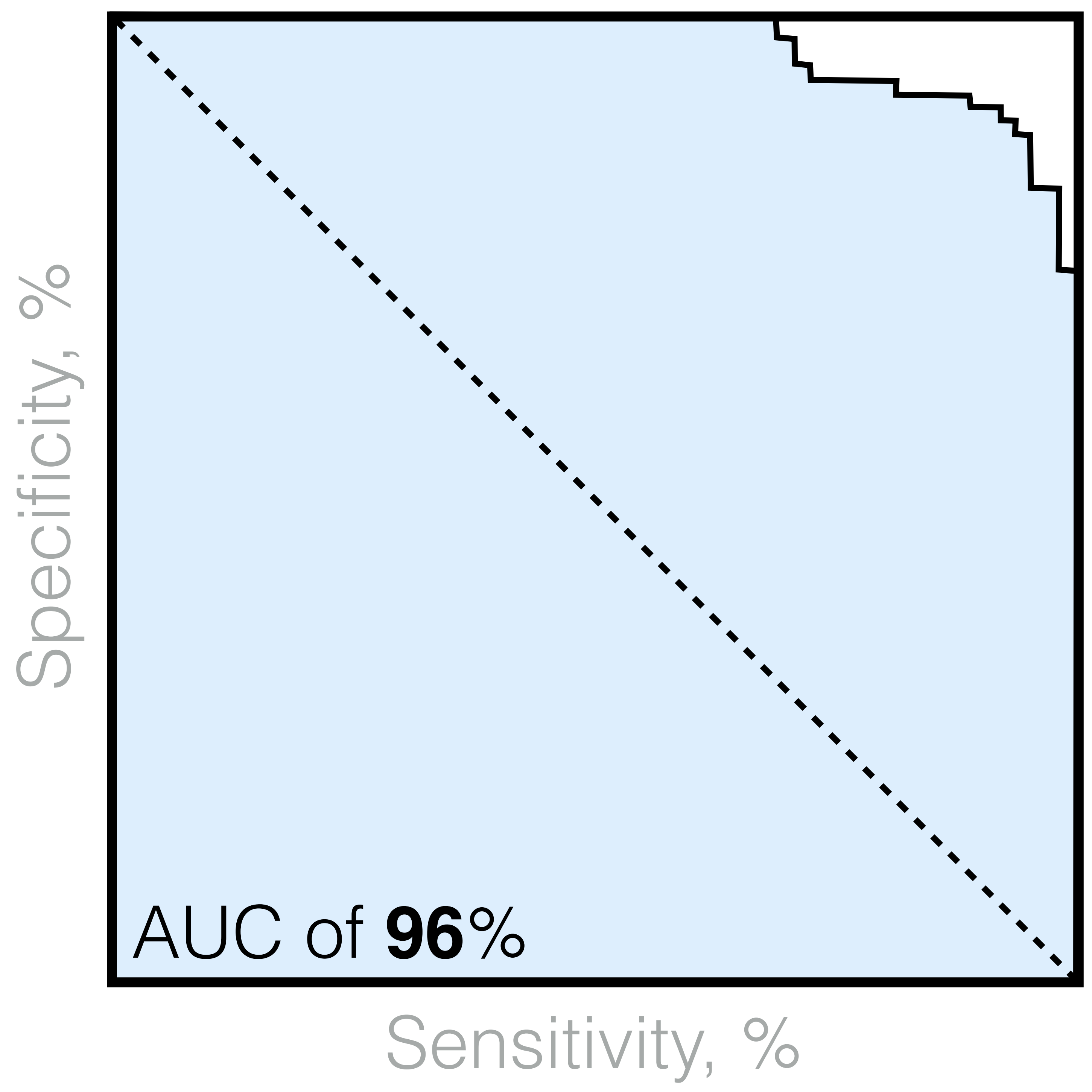
Epidermal
Squamous cell carcinoma
Basal cell carcinoma
Lipoma
Fibroma
Dermal
Cyst
Epidermal
Melanocytic
Milia
Seborrhoeic keratosis
Solar lentigo
Café au lait spot
Atypical nevus

Algorithm vs Dermatologists

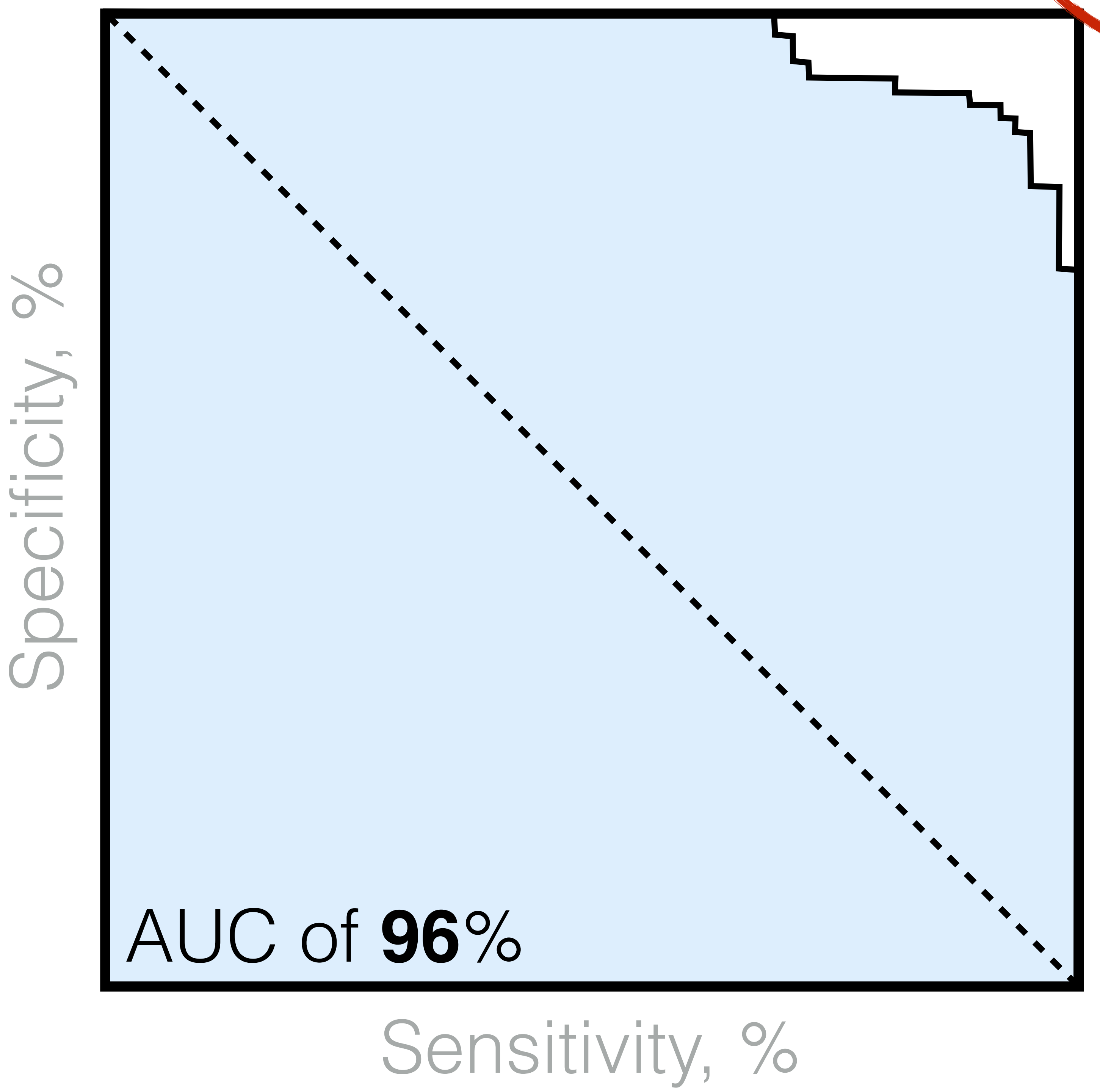
Algorithm vs Dermatologists

Carcinoma: 135 images

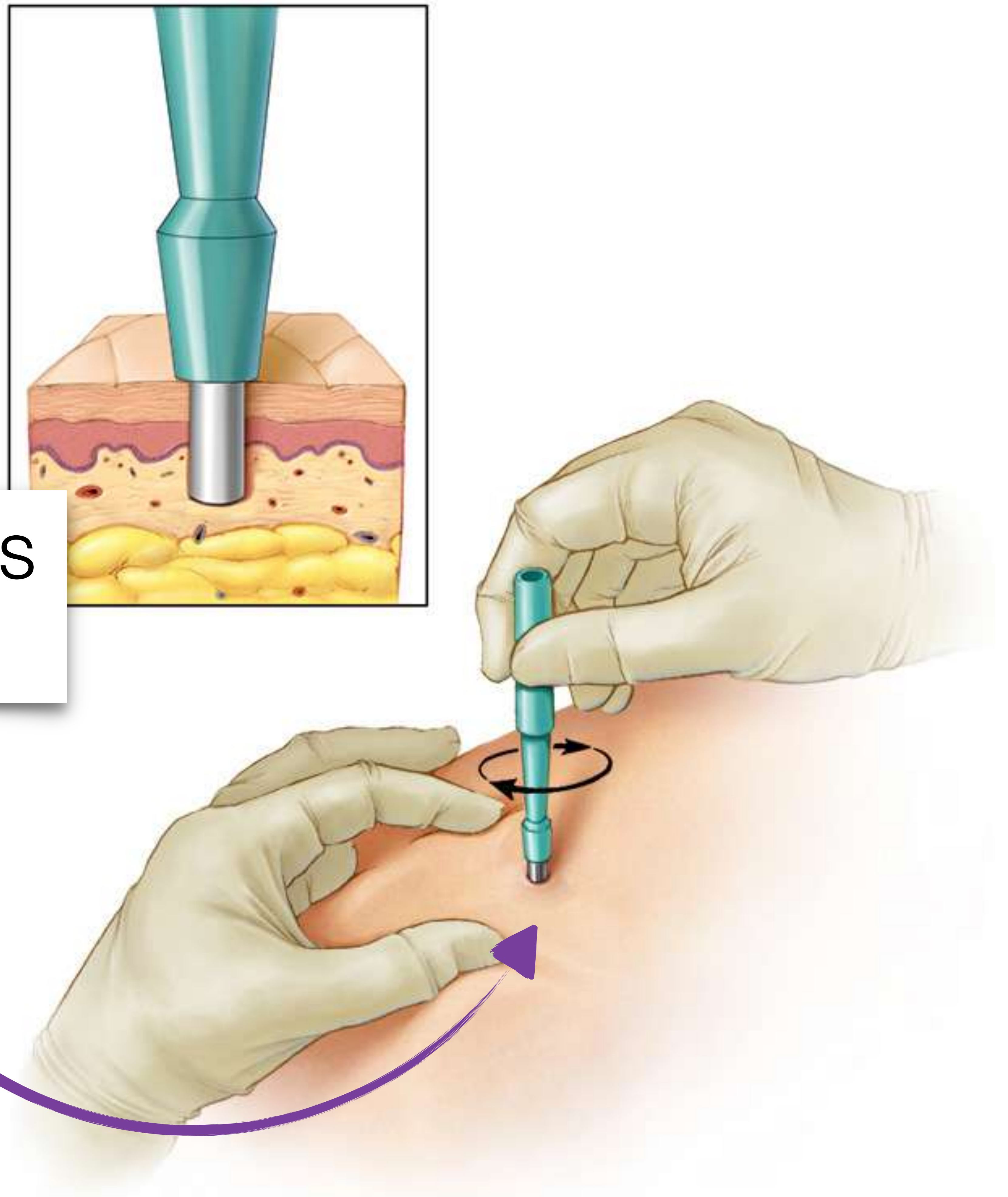


Algorithm vs Dermatologists

Carcinoma: **135 images**

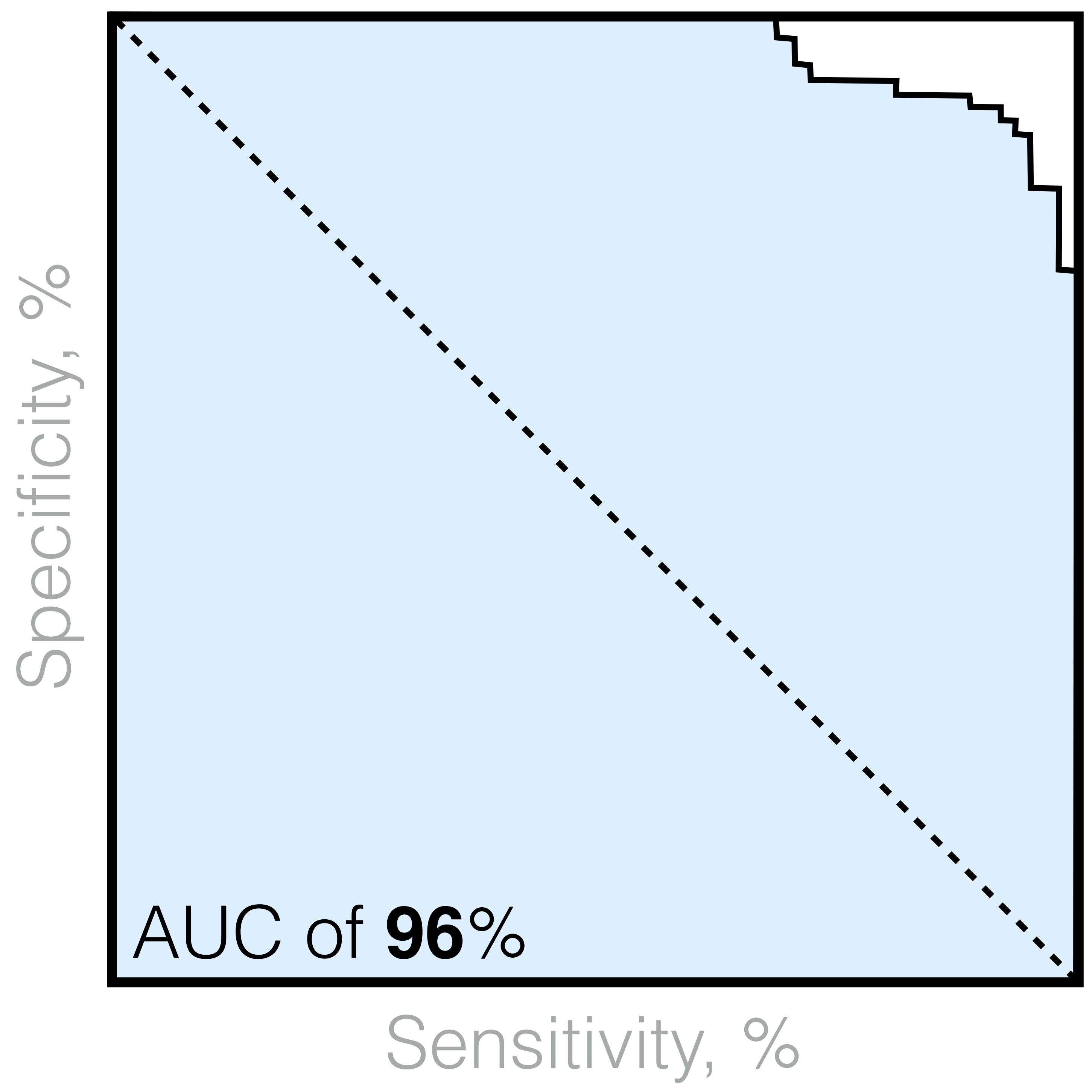


Each of the **cases** was verified by **biopsy**



Algorithm vs Dermatologists

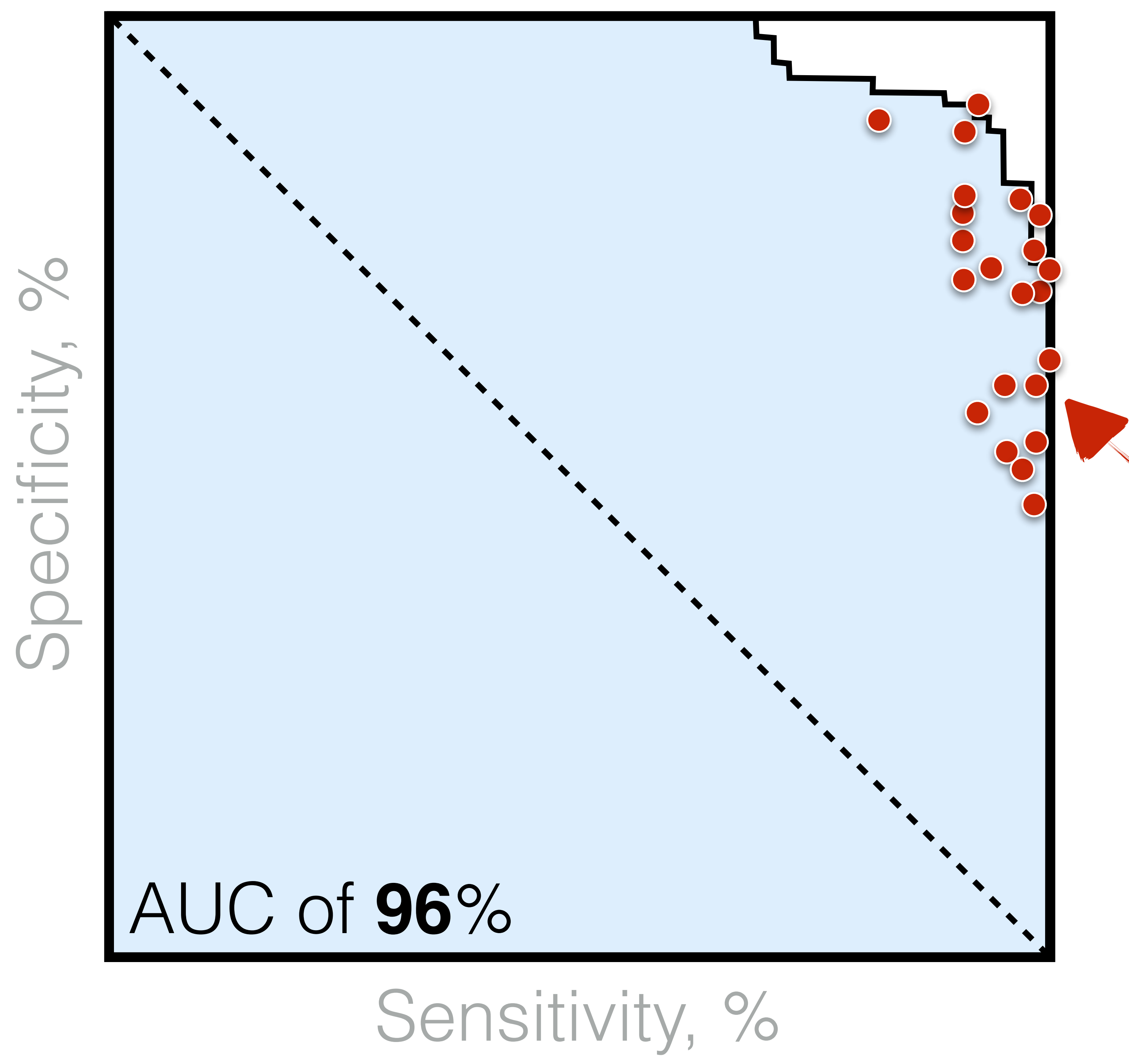
Carcinoma: 135 images



Algorithm vs Dermatologists

Carcinoma: 135 images

Dermatologists (**25**)

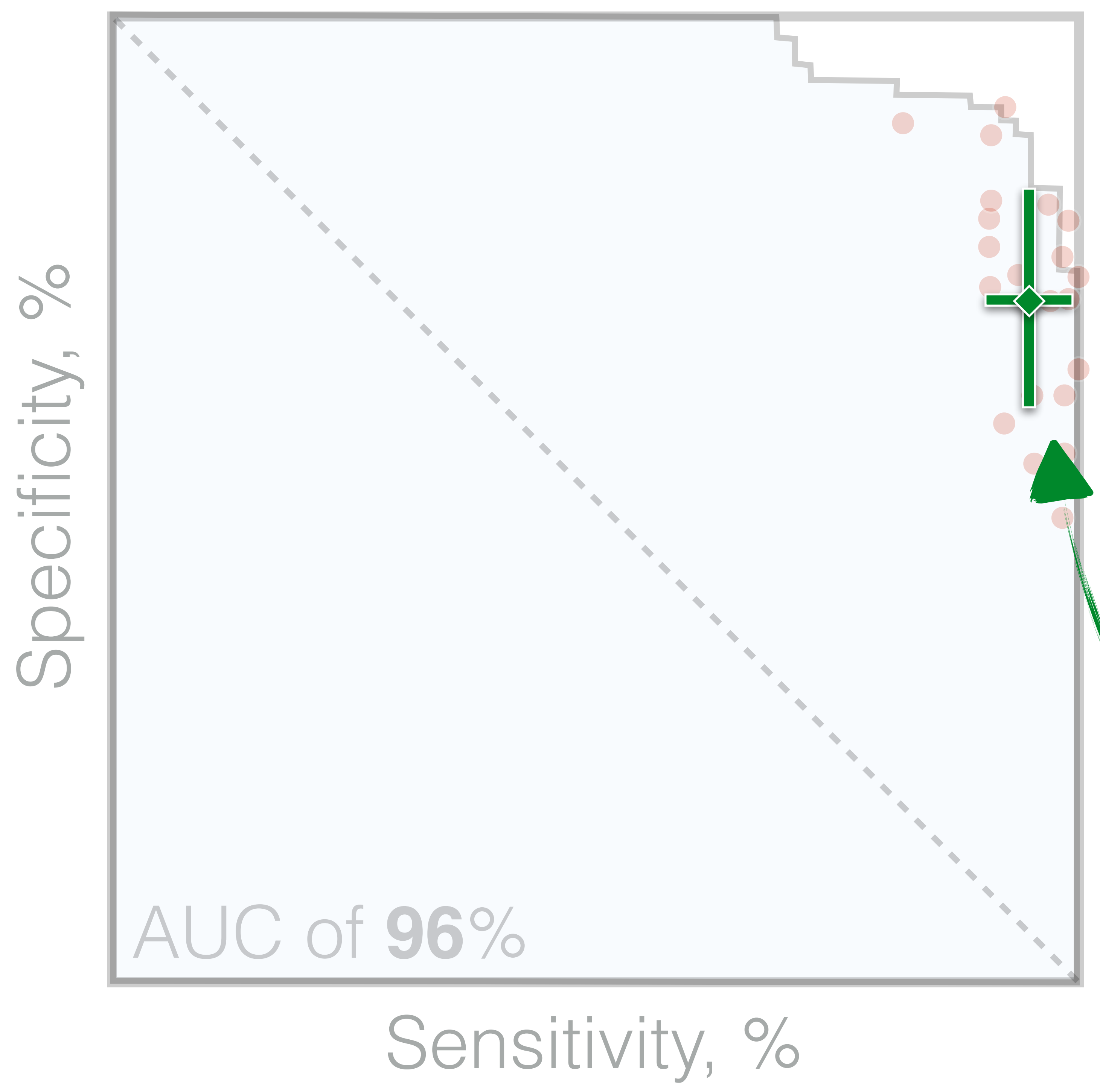


Performance of the algorithm was compared to **dermatologists**

Algorithm vs Dermatologists

Carcinoma: 135 images

Dermatologists (25)



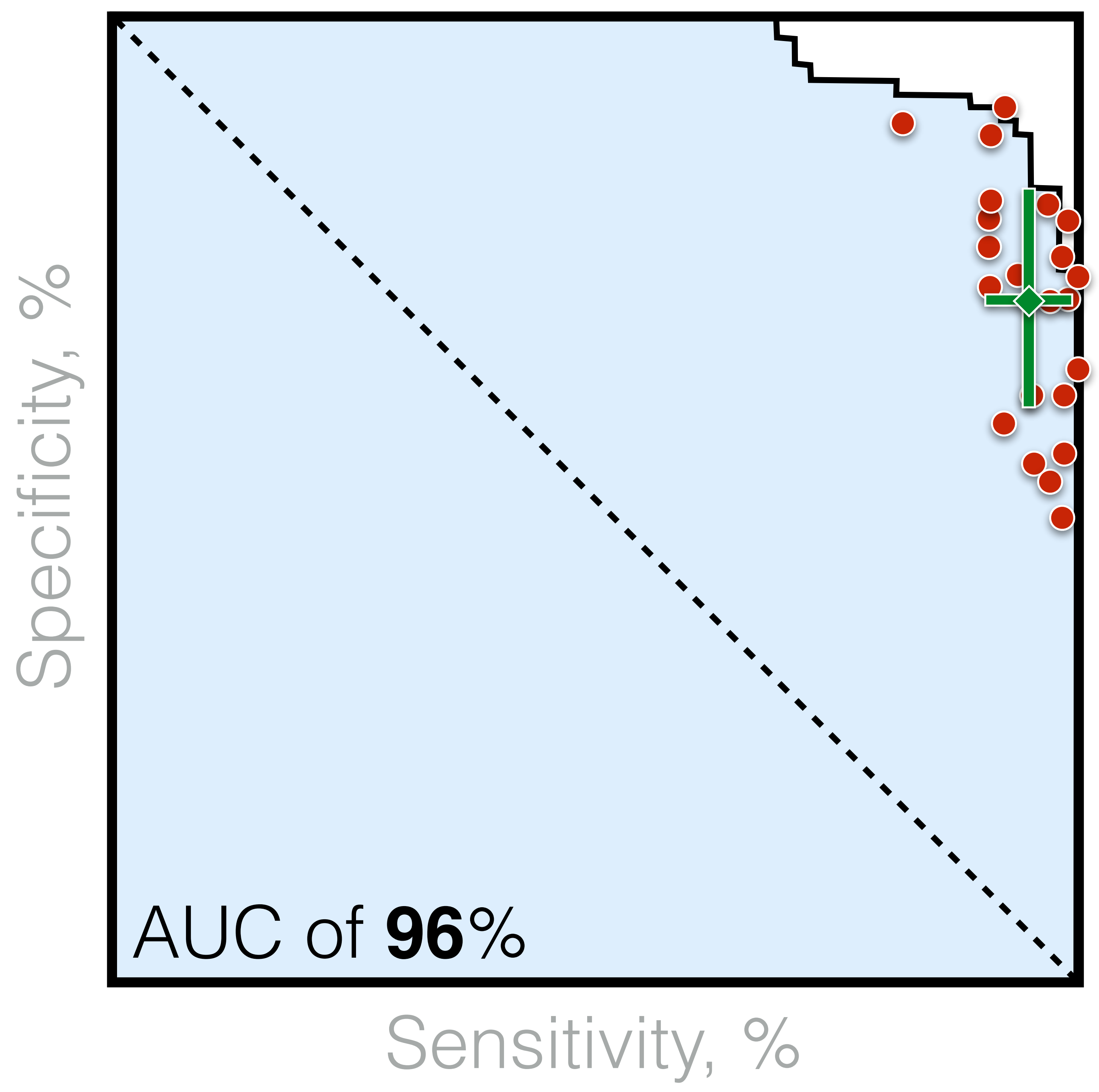
Performance of the algorithm was compared to **dermatologists**

Average dermatologist's performance was marked as

Algorithm vs Dermatologists

Carcinoma: 135 images

Dermatologists (25)



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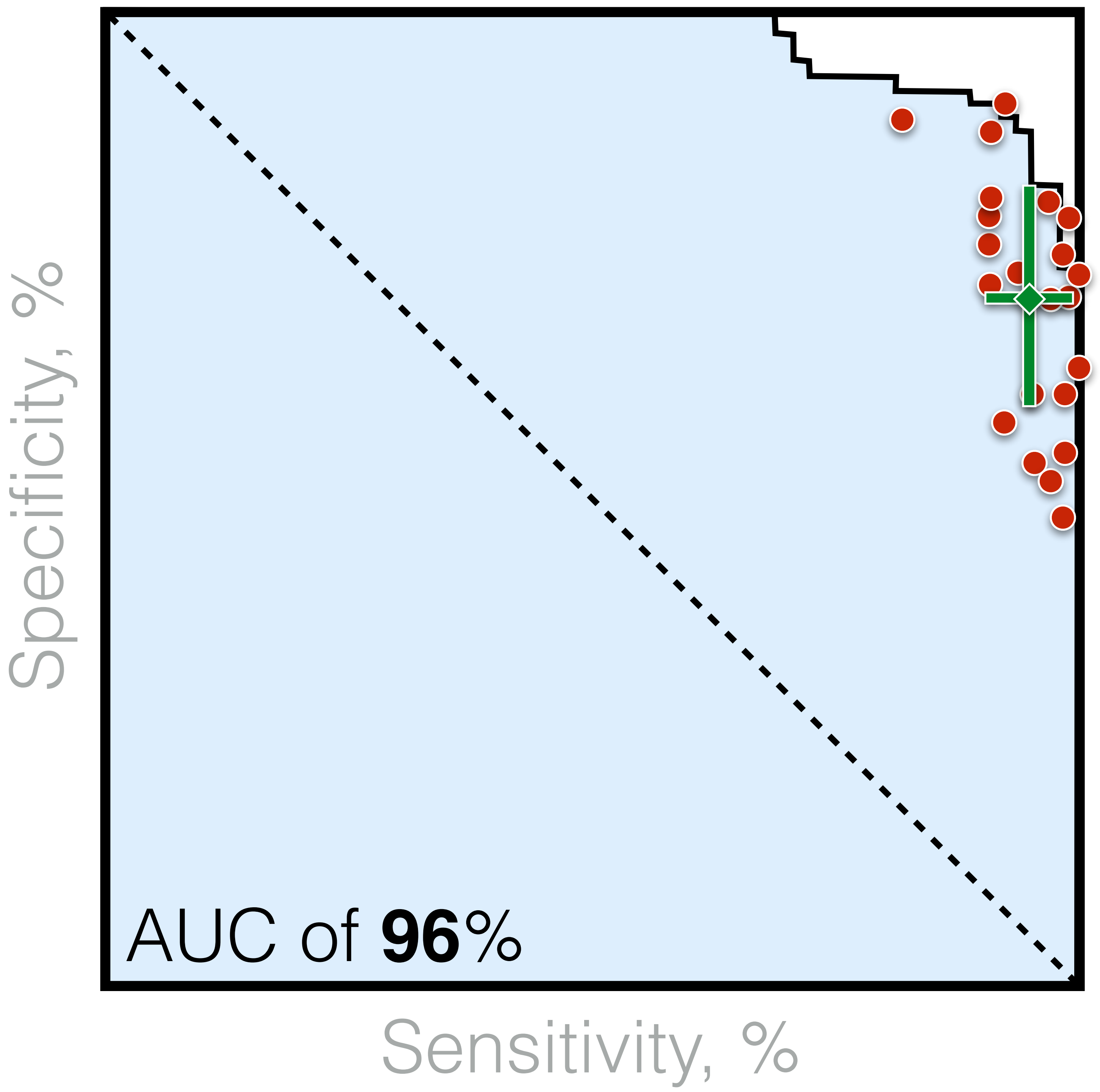
Algorithm vs Dermatologists

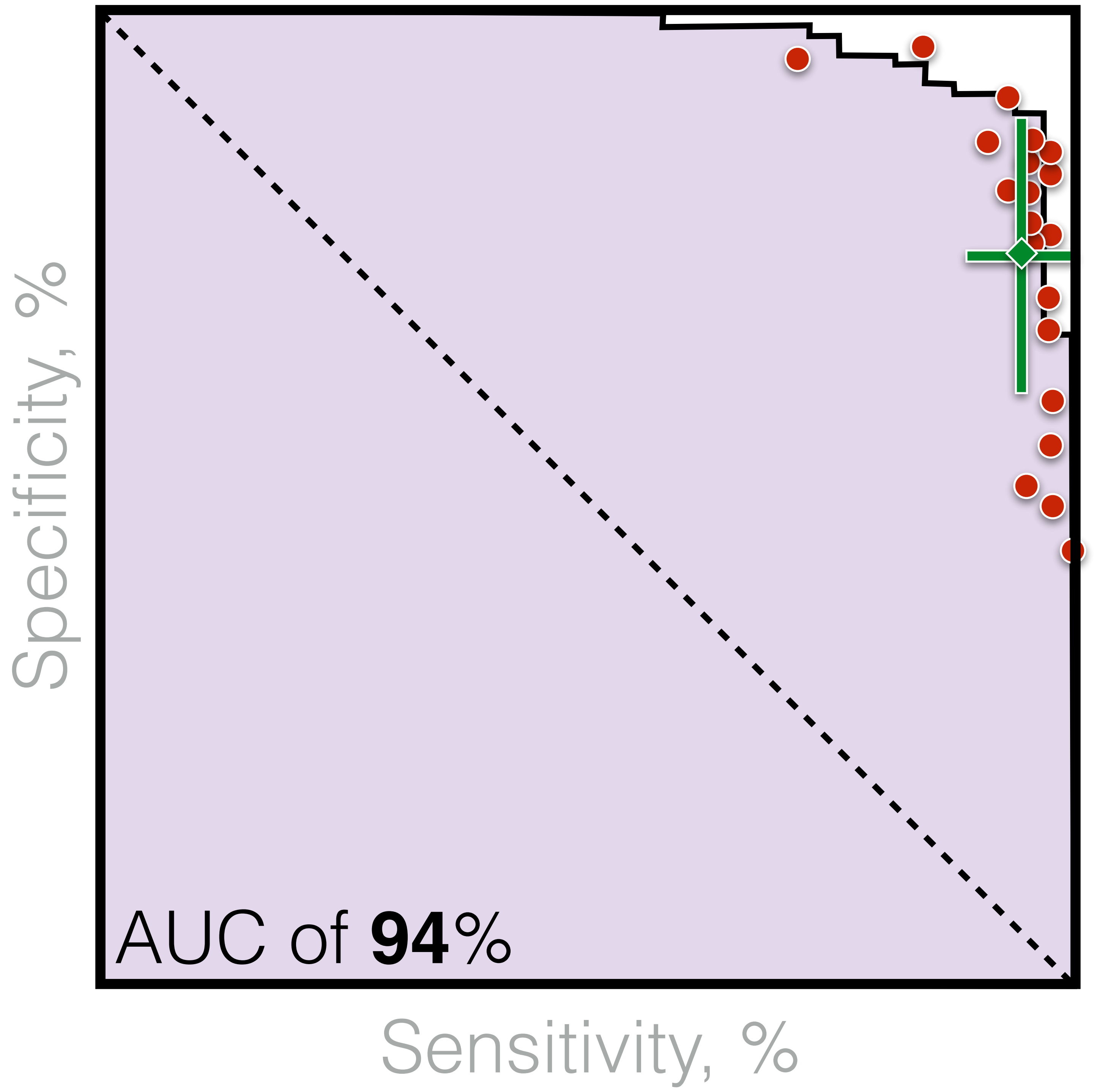
Carcinoma: 135 images

Dermatologists (25)



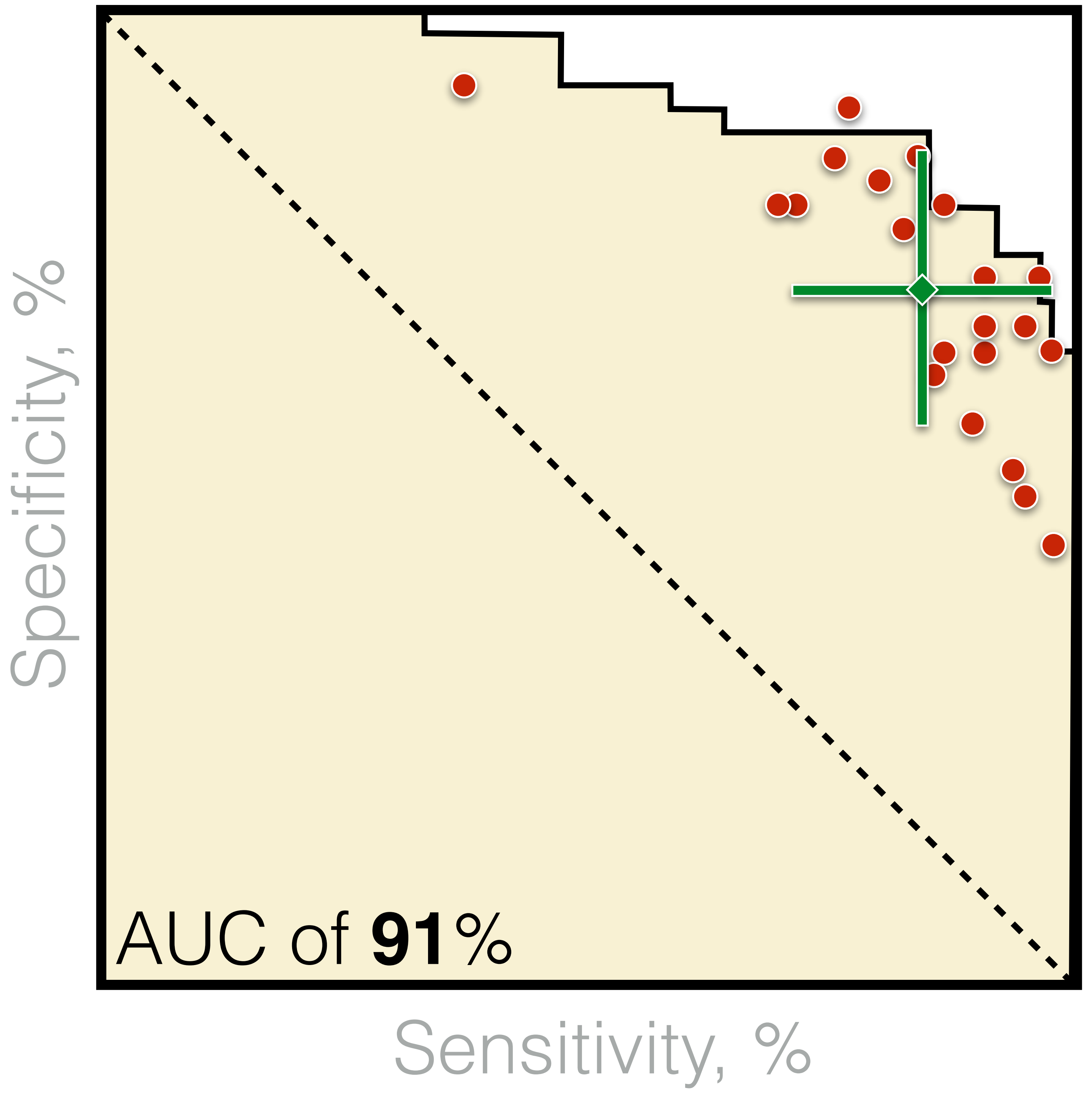
Melanoma: 130 images

Dermatologists (22)

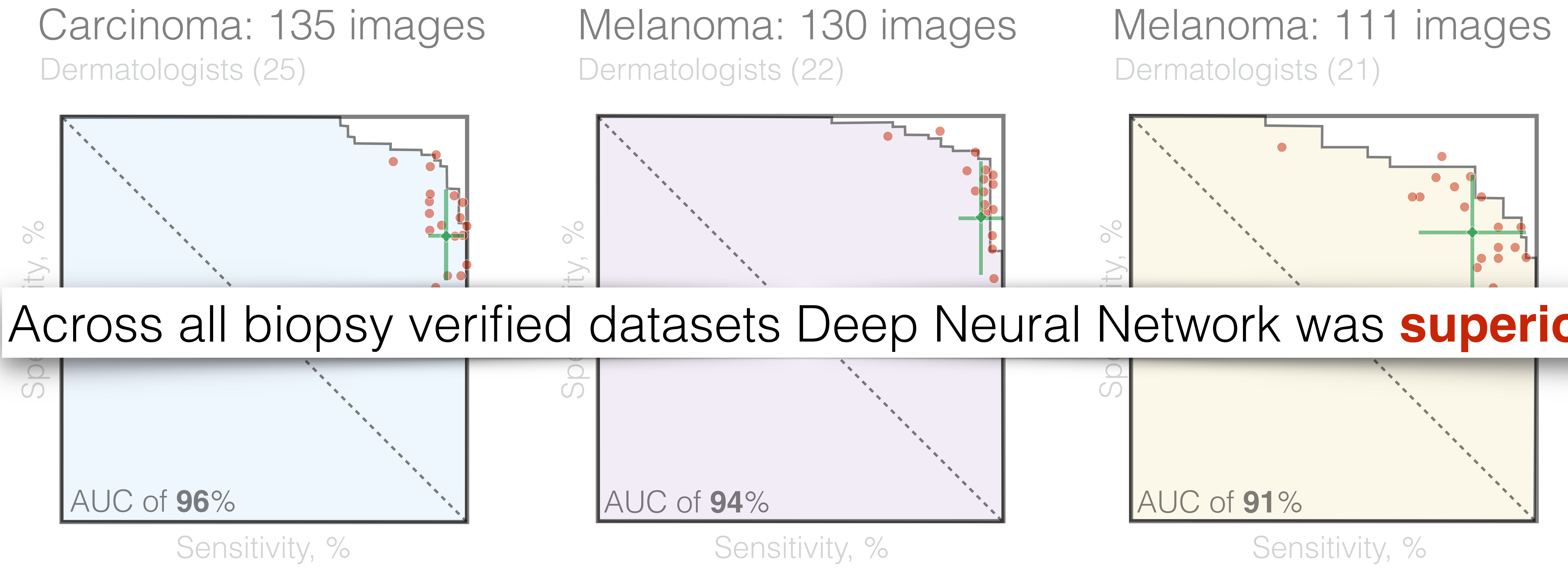


Melanoma: 111 images

Dermatologists (21)



Algorithm vs Dermatologists



Across all biopsy verified datasets Deep Neural Network was **superior**

Diabetic Retinopathy

Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs

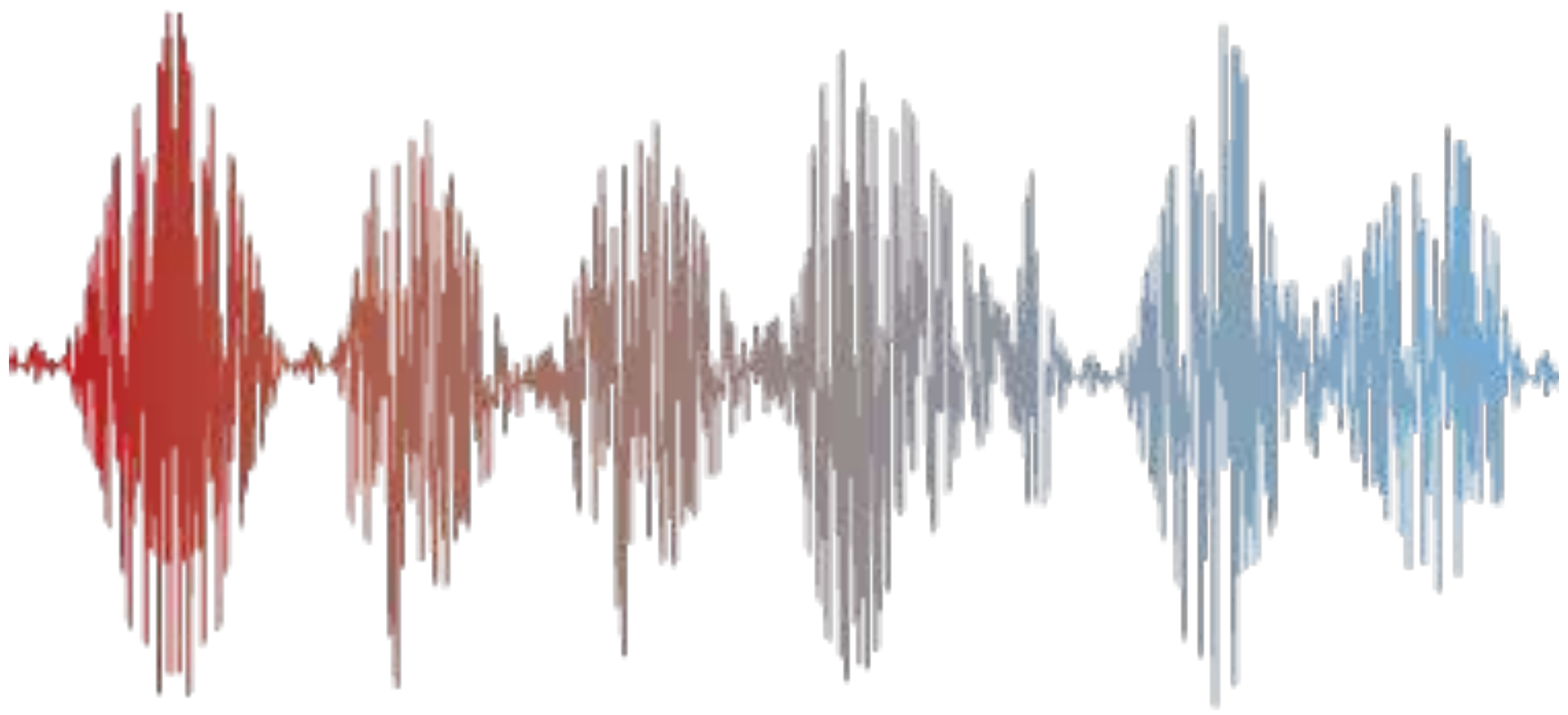
https://jamanetwork.com/journals/jama/fullarticle/2588763

Skin Cancer

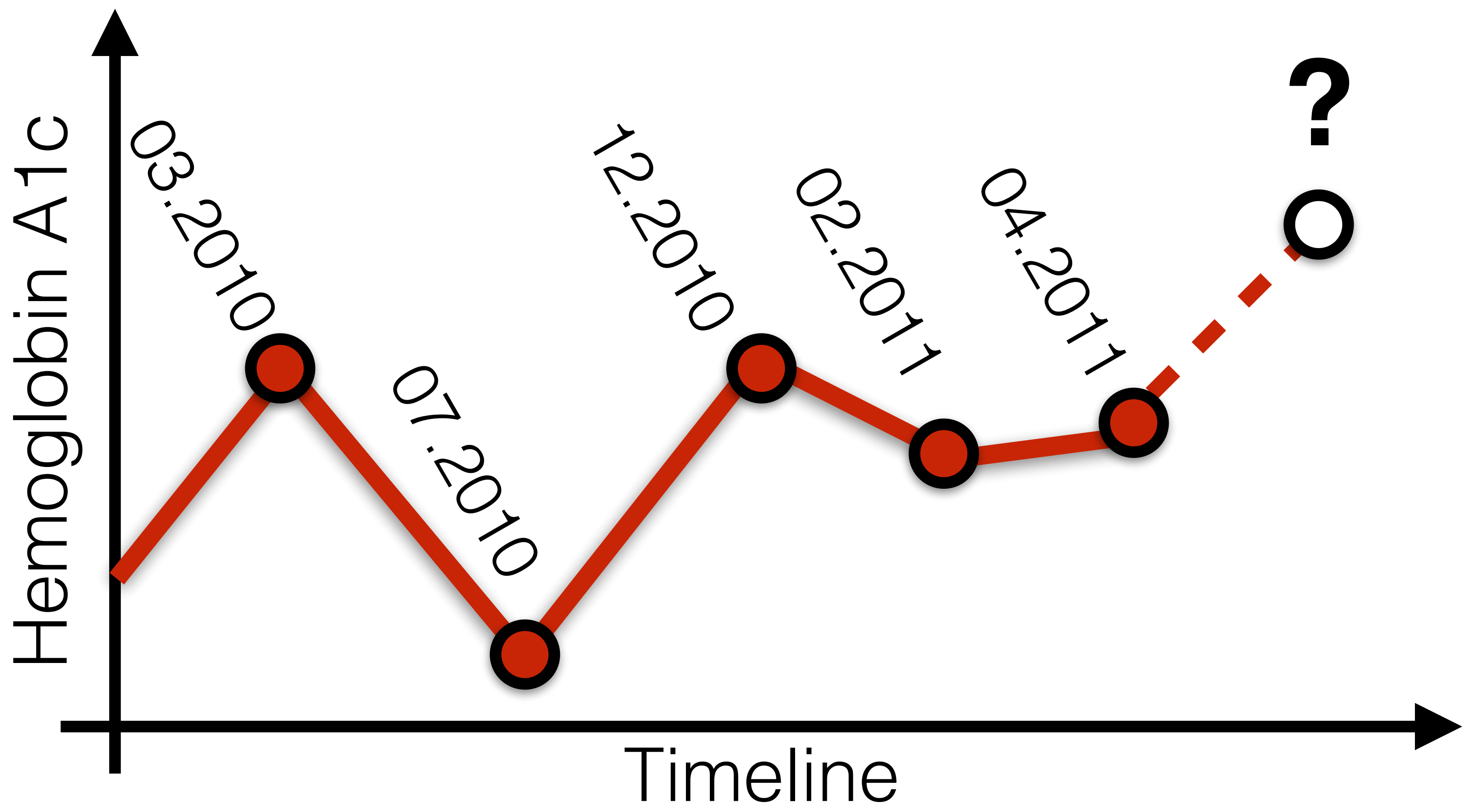
Dermatologist-level classification of skin cancer with deep neural networks

https://www.nature.com/nature/journal/v542/n7639/full/nature21056.html

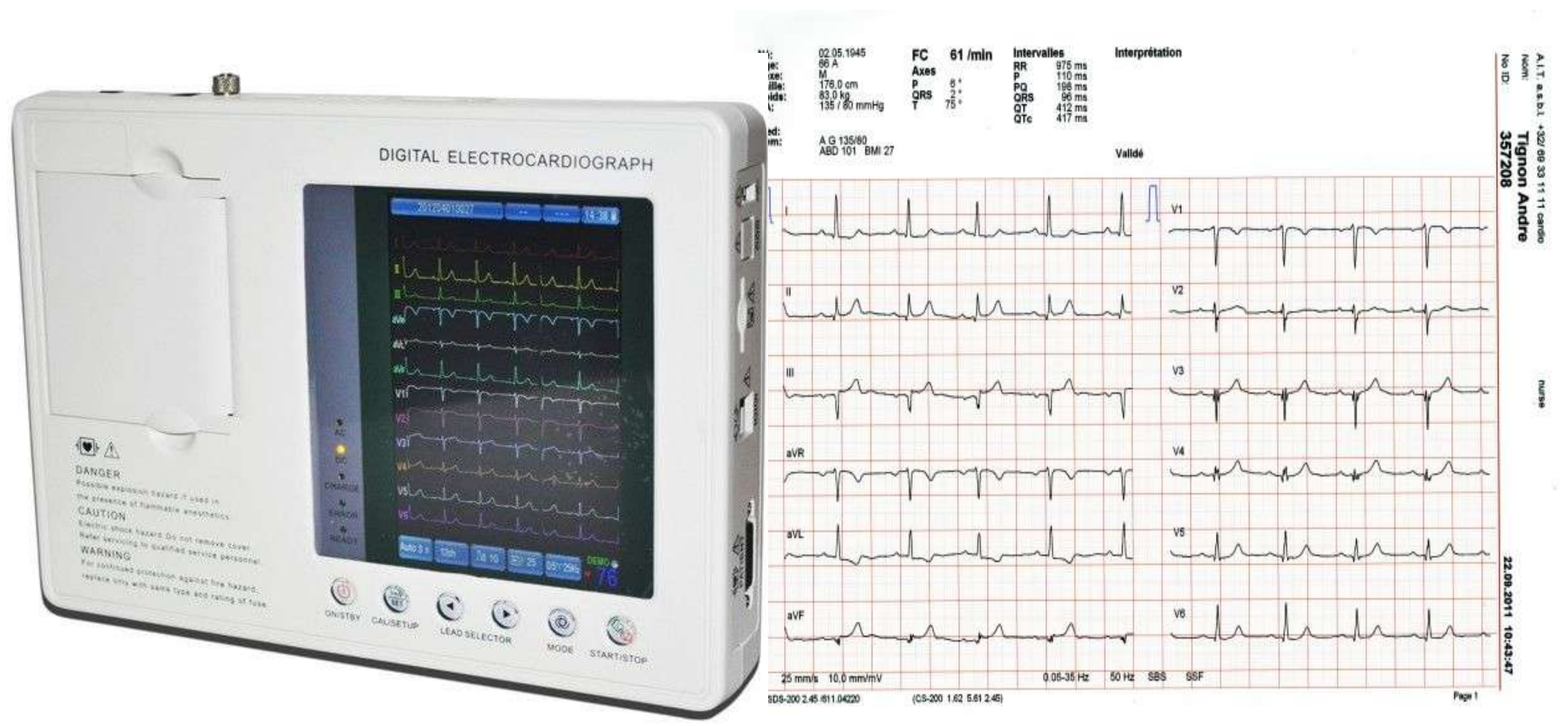
Few more interesting applications



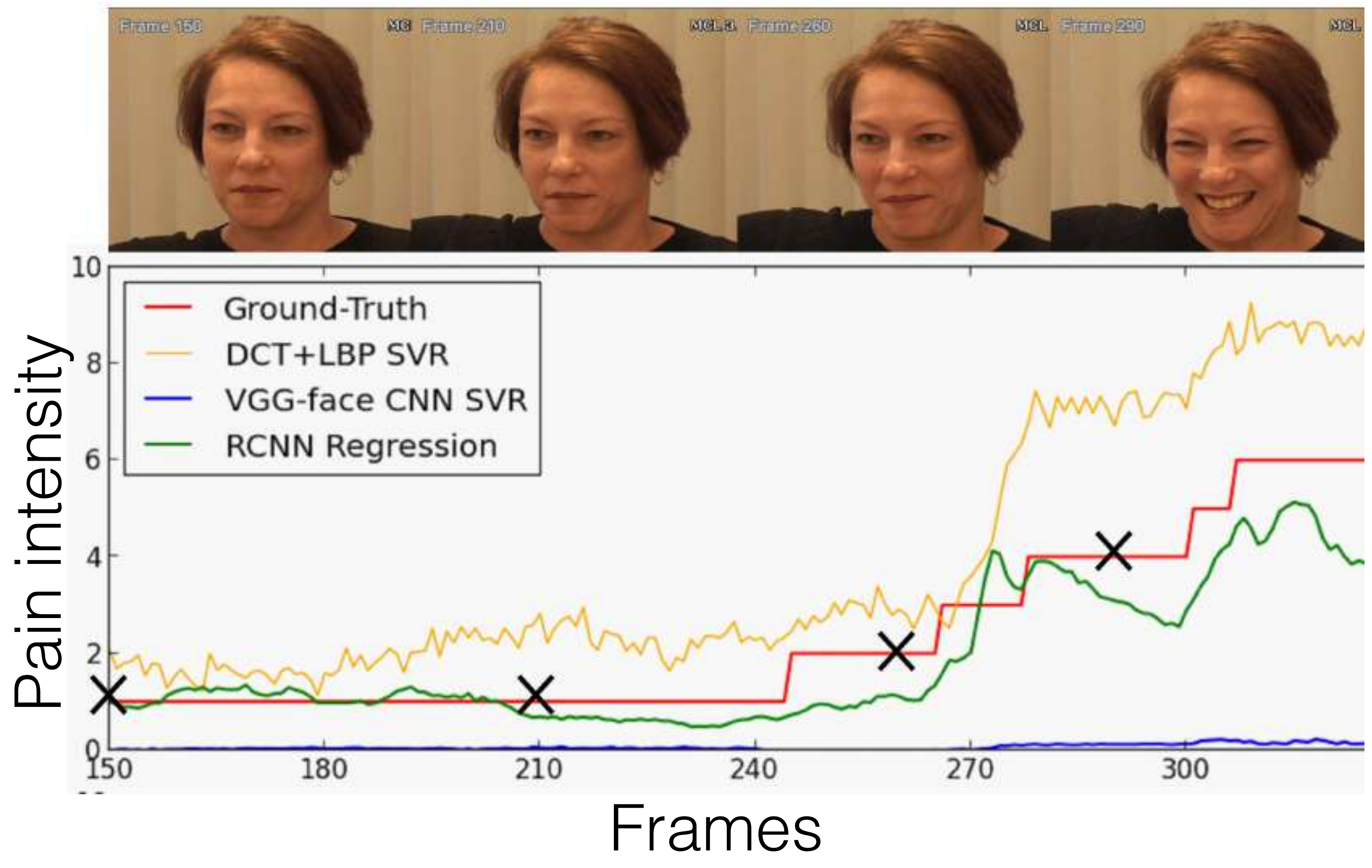
Diagnosing Parkinson from voice
(Al-Fatlawi et al., 2016)



Predicting subsequent hospitalisation (Choi et al., 2016)



Detection of hypoglycemic episodes in children
(San et al., 2016)



Pain estimation from video
(Zhou et al., 2016)

Application of Deep Learning for Recognizing Infant Cries

Chuan-Yu Chang, Jia-Jing Li
National Yunlin University of Science & Technology, Taiwan
E-mail: chuanyu@yuntech.edu.tw

***Abstract*--Crying is a way which infants express their needs to their parents. In general, parents often feel worried and anxious when infant crying. For realizing the reason of baby crying, this paper presents an automatic infant crying recognition method. Crying is convert to spectrogram. A convolutional neural networks (CNN) based deep learning is then adopted to train and classify the crying into three categories including hungry, pain, and sleepy. Experimental results shows that the proposed method achieves high classification accuracy.**

I. Introduction

In recent years, deep learning with capability of high-level abstraction had been widely applied to image recognition and speech recognition [4]. There are many deep learning algorithms had been proposed such as restricted Boltzmann machine (RBM), convolutional neuron networks (CNN), deep belief networks (DBN), and deep neuron networks (DNN). Those deep learning algorithms have applied to many applications successfully.

the training data. Dropout improves the performance of neural networks on supervised learning tasks. Figure 1(a) and (b) shows the structure of the original network and the network adopted dropout technology, respectively.

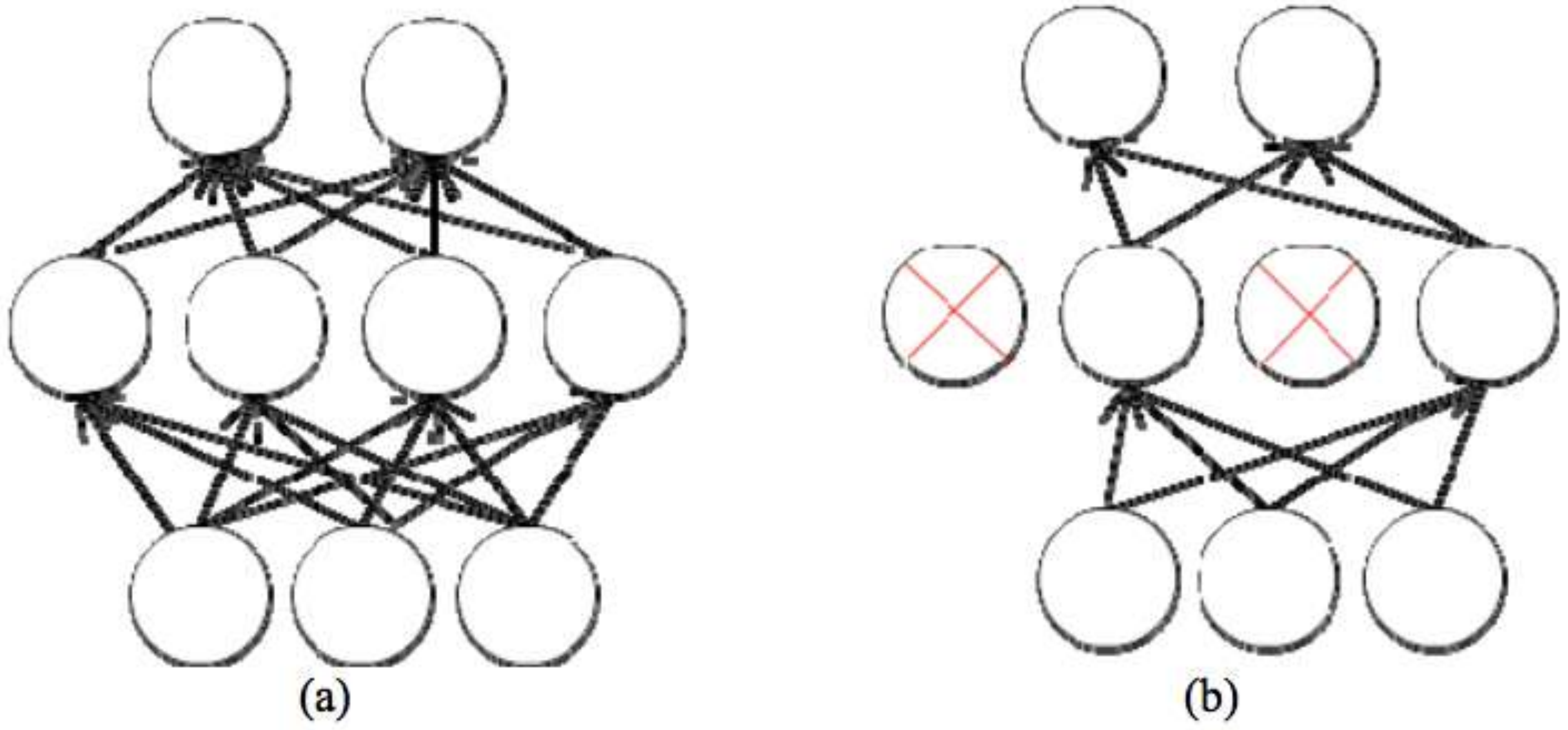


Fig. 1. (a) is a normal neural network, (b) adopted dropout learning in the neural network.

Application of Deep Learning for Recognizing Infant Cries

ng, Jia-Jing Li
cience & Technology, Taiwan
@yuntech.edu.tw

belief networks (DBN), and deep neuron networks (DNN). Those deep learning algorithms have applied to many applications successfully.

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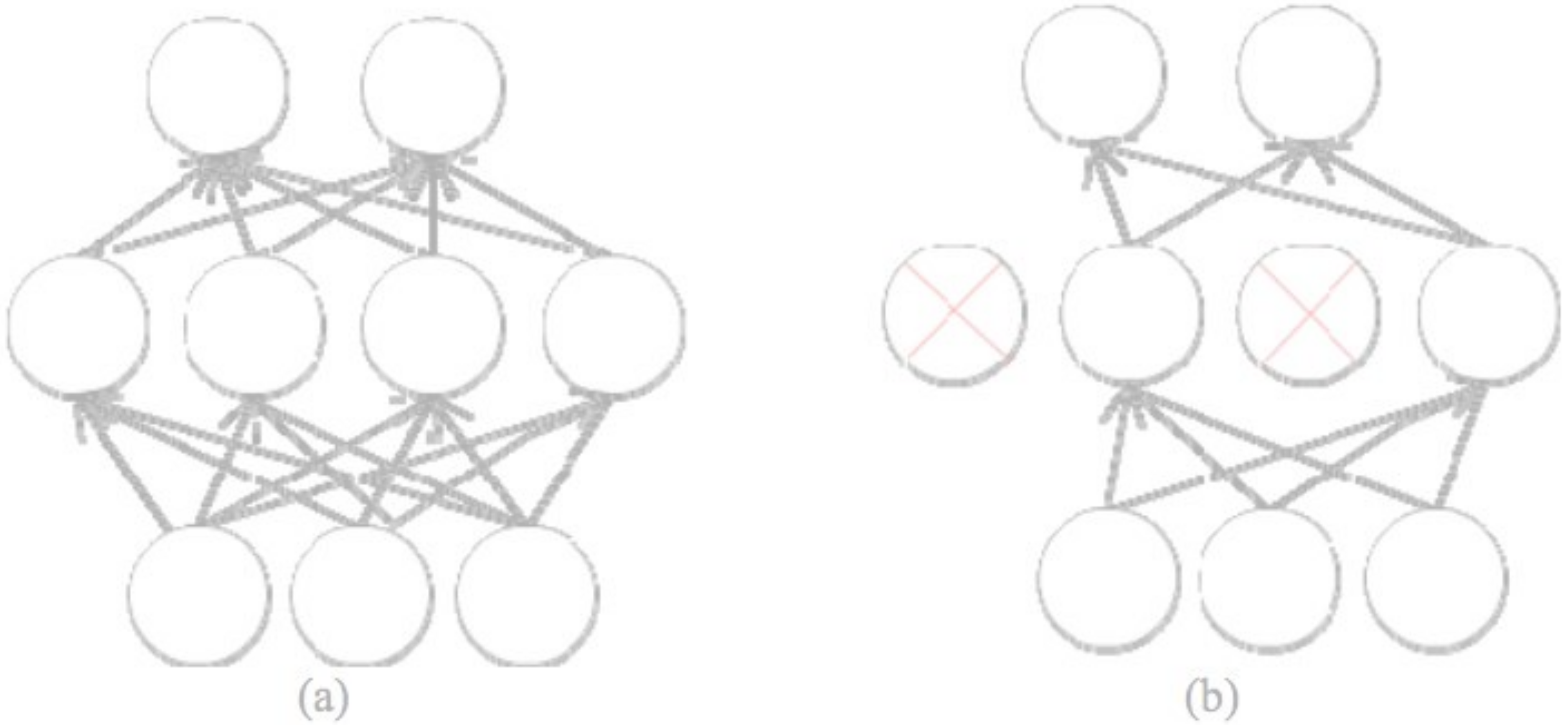

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(a) (b)

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2016 International Conference on Consumer Electronics-Taiwan

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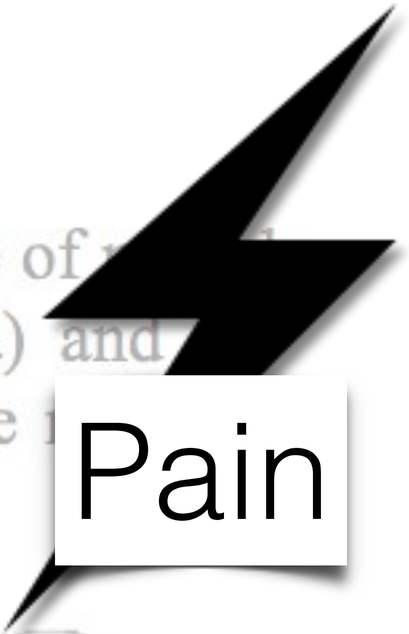

(a) (b)

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netwo ... Figure 1(a) and
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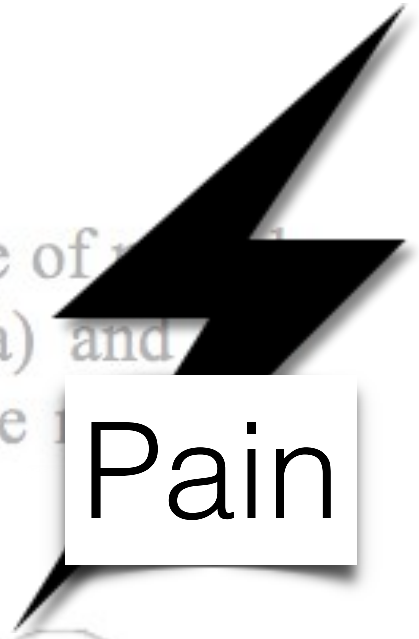
adopte ... y.



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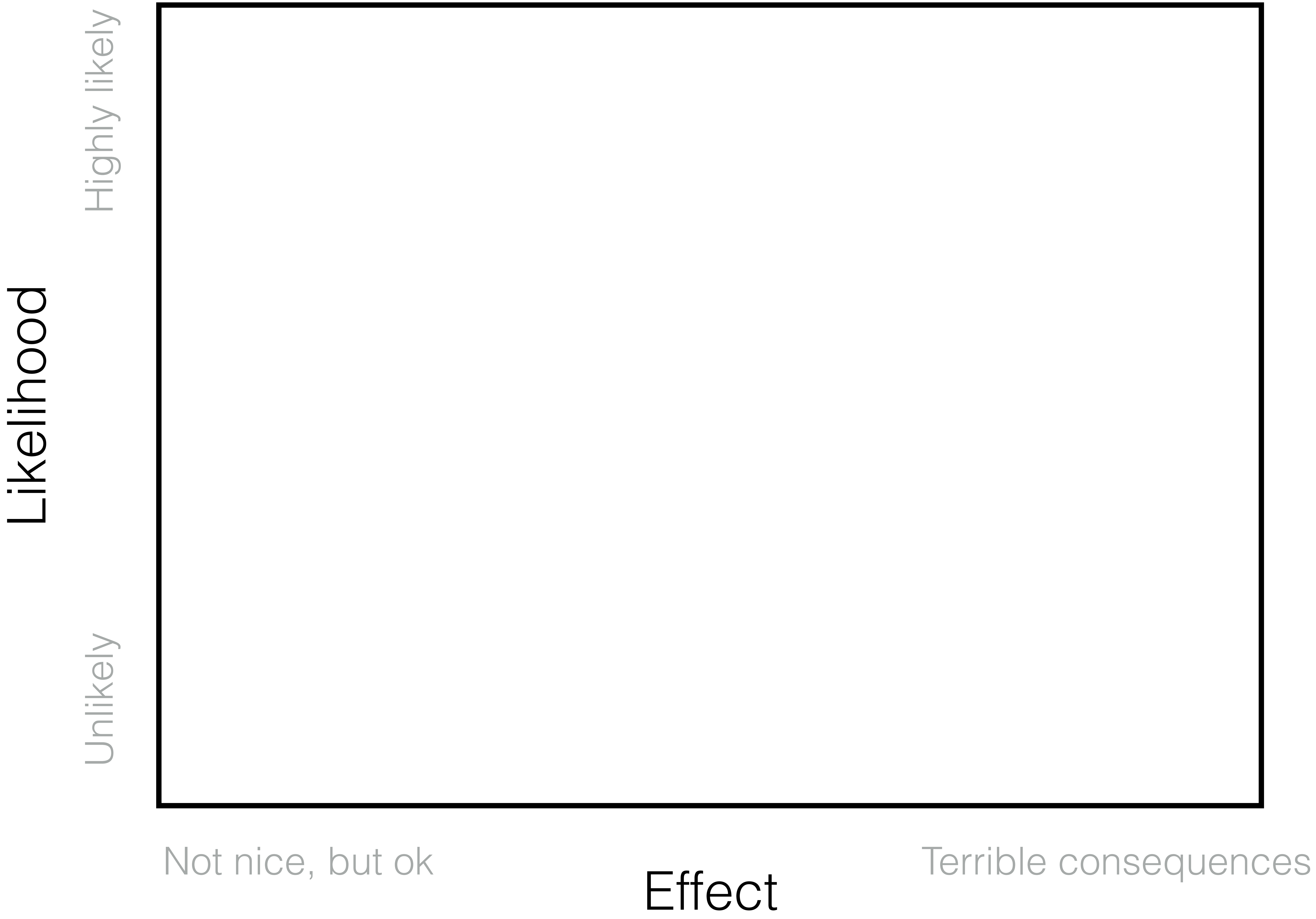
(a) (b)

Fig. 1. (a) is a normal neural network, (b) adopted dropout learning in the neural network.

Seems like revolution has not happened

Why Deep Learning **has not** revolutionised **medicine** yet?

Chart of possible reasons why deep learning may fail to revolutionise medicine



We may fail to compose large enough datasets

We may fail to compose large enough datasets

$

Collecting data in
medicine
is very expensive

We may fail to compose large enough datasets

Collecting data in
medicine
is very expensive

Medical data is often
protected (for a good
reason)

We may fail to compose large enough datasets

We may fail to compose large enough datasets

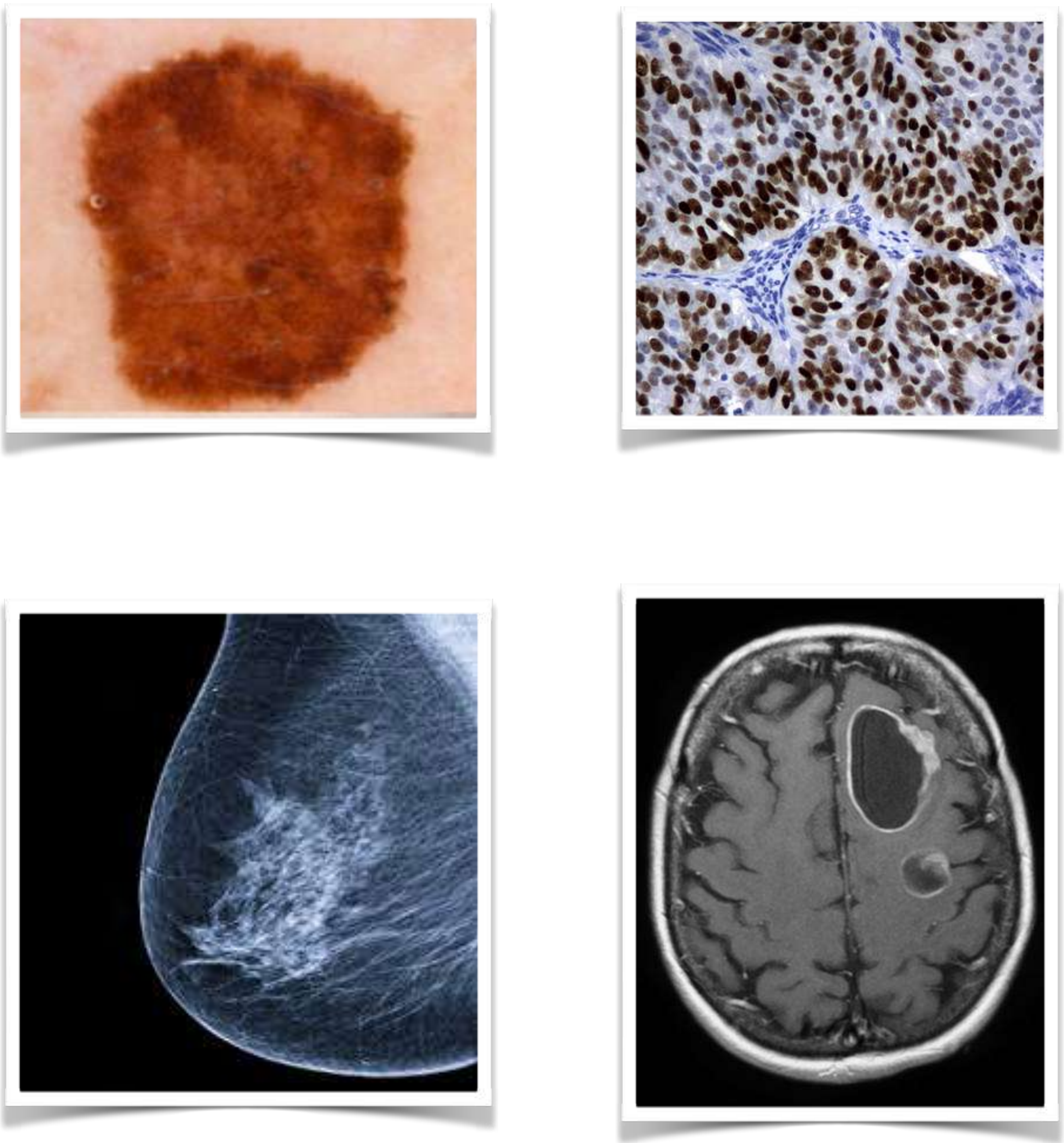
We may fail to compose large enough datasets

We may fail to compose large enough datasets

We can build a model that can distinguish them from other objects

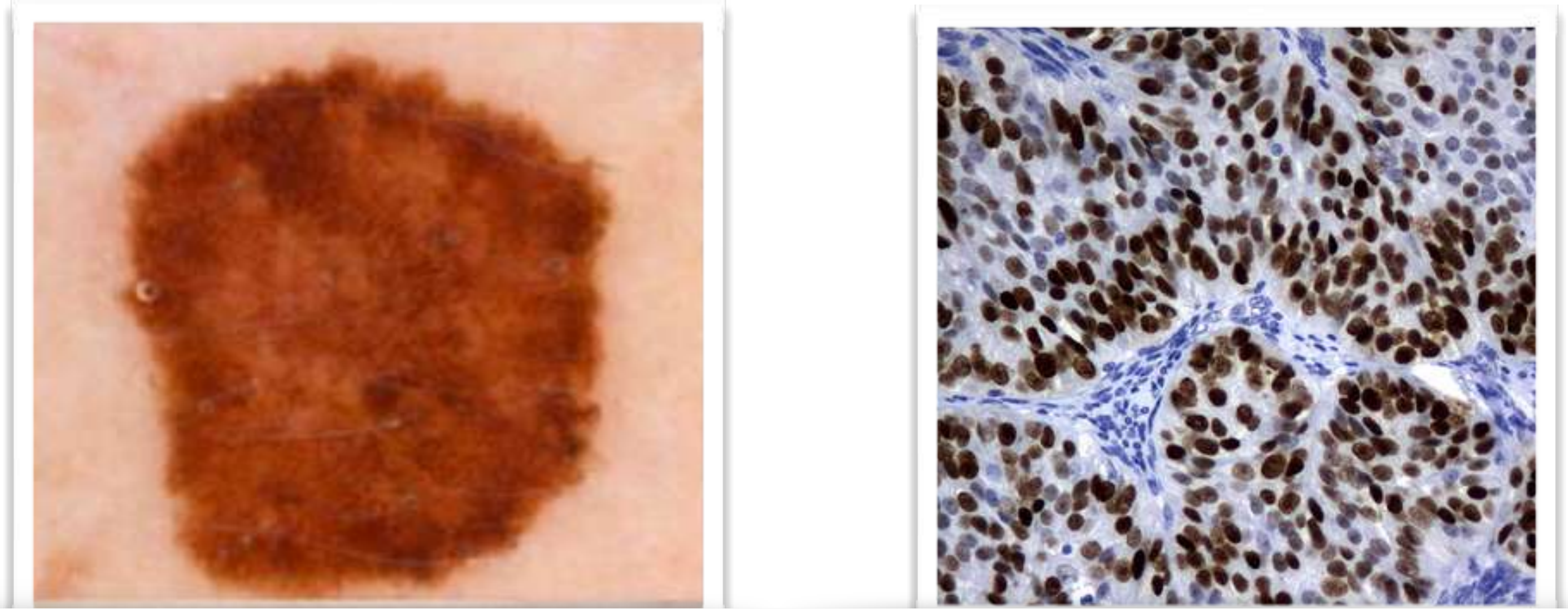
We may fail to compose large enough datasets

We can build a model that can distinguish them from other objects

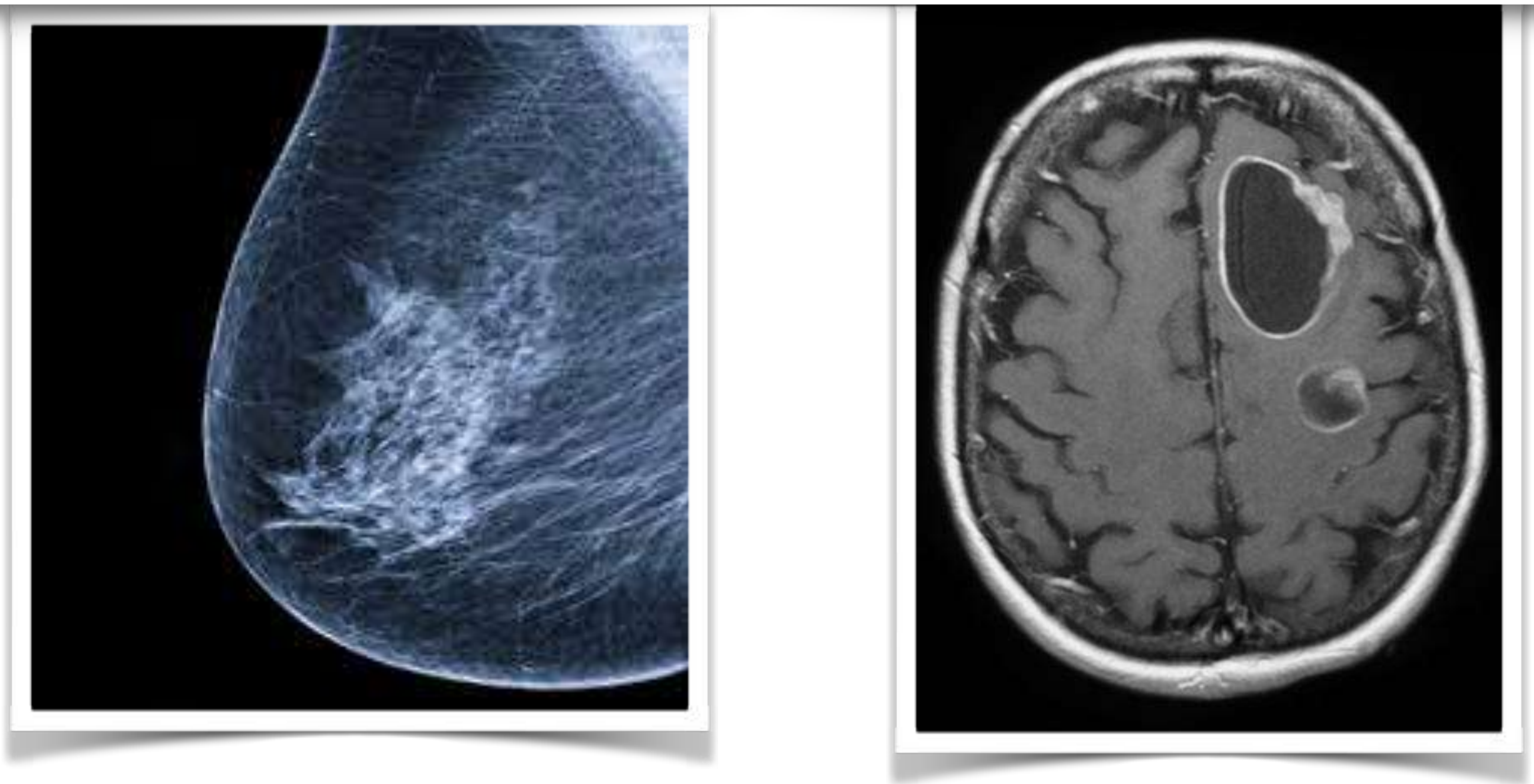


We may fail to compose large enough datasets

We can build a model that can distinguish them from other objects

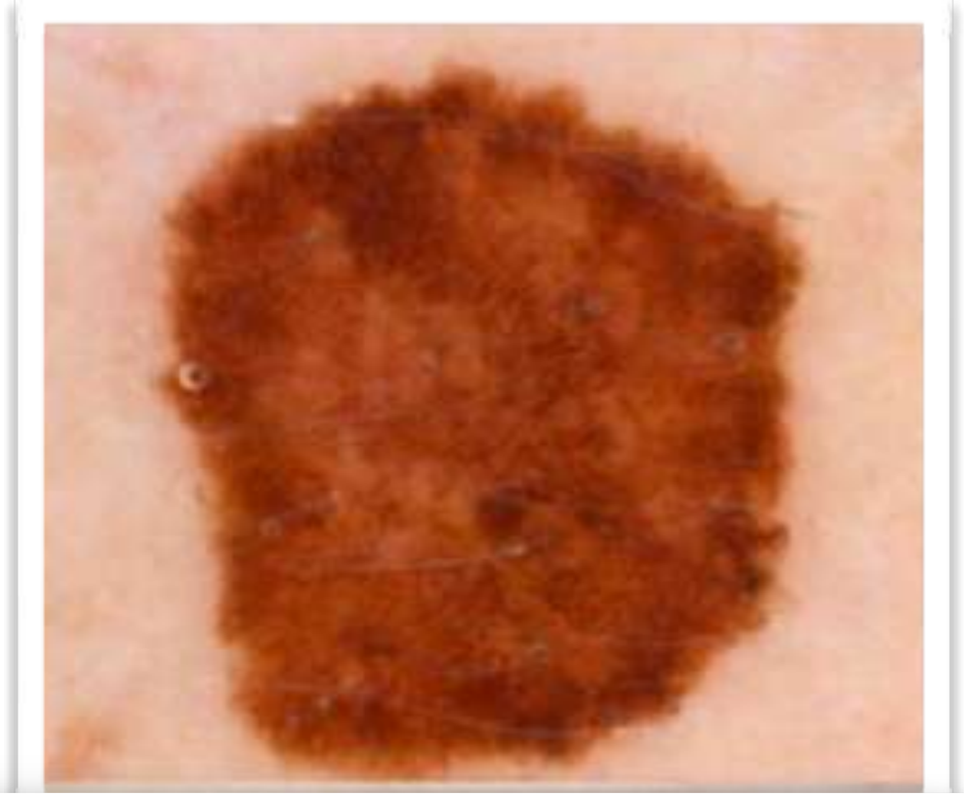
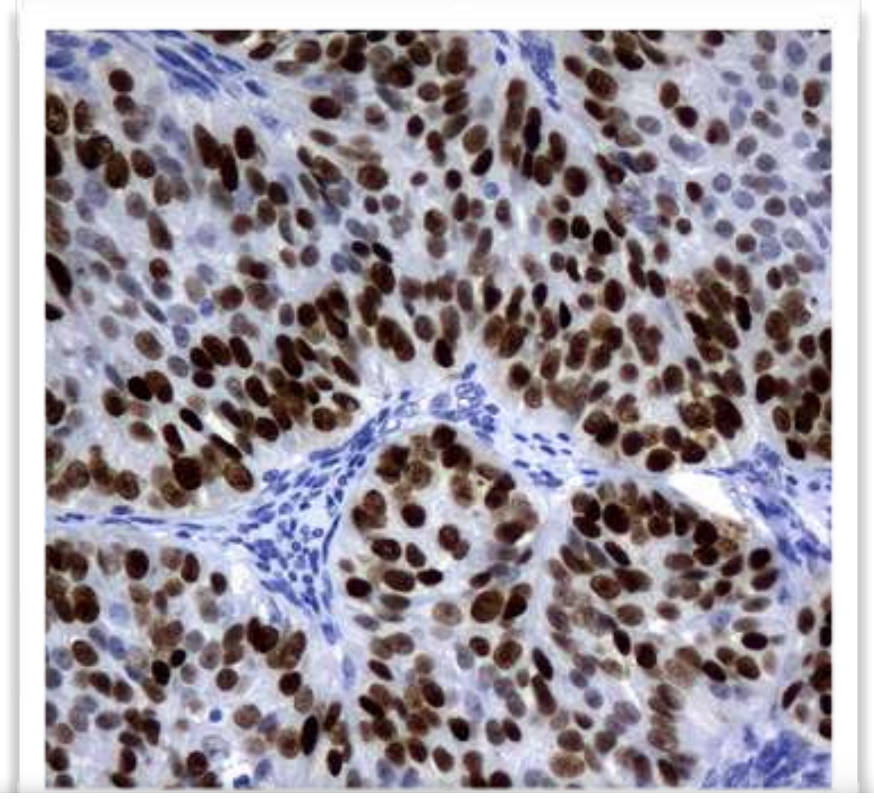


Most of the cancers have different appearance



We may fail to compose large enough datasets


We can build a model that can distinguish them from other objects

Most of the cancers have different appearance


We would need a separate **ImageNet** for all of them

Radiology Informatics   Home   About   Members   Projects

Medical Image Net

A petabyte-scale, cloud-based, multi-institutional, searchable, open repository of diagnostic imaging studies for developing intelligent image analysis systems.

AREAS OF RESEARCH

- Deep Learning
- Imaging Informatics
- Machine Learning

DATASETS

- Imaging Datasets
- Natural Language Datasets

Featured Goals

Possible solution

- Data migration/federation/honest broker
- Linkage to EMR and multi-omics
- Cohort discovery tools
- Image viewing software
- Governance
- Image classification and annotation
  - Natural language processing, research data sets, crowd source

Stanford MEDICINE

http://langlotzlab.stanford.edu/projects/medical-image-net/

Medical Image Net

A petabyte-scale, cloud-based, multi-institutional, searchable, open repository of diagnostic imaging studies for developing intelligent image analysis systems.

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Deep Learning
Imaging Informatics
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DATASETS

Imaging Datasets
Natural Language Datasets

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- Data migration/federation/honest broker
- Linkage to EMR and multi-omics
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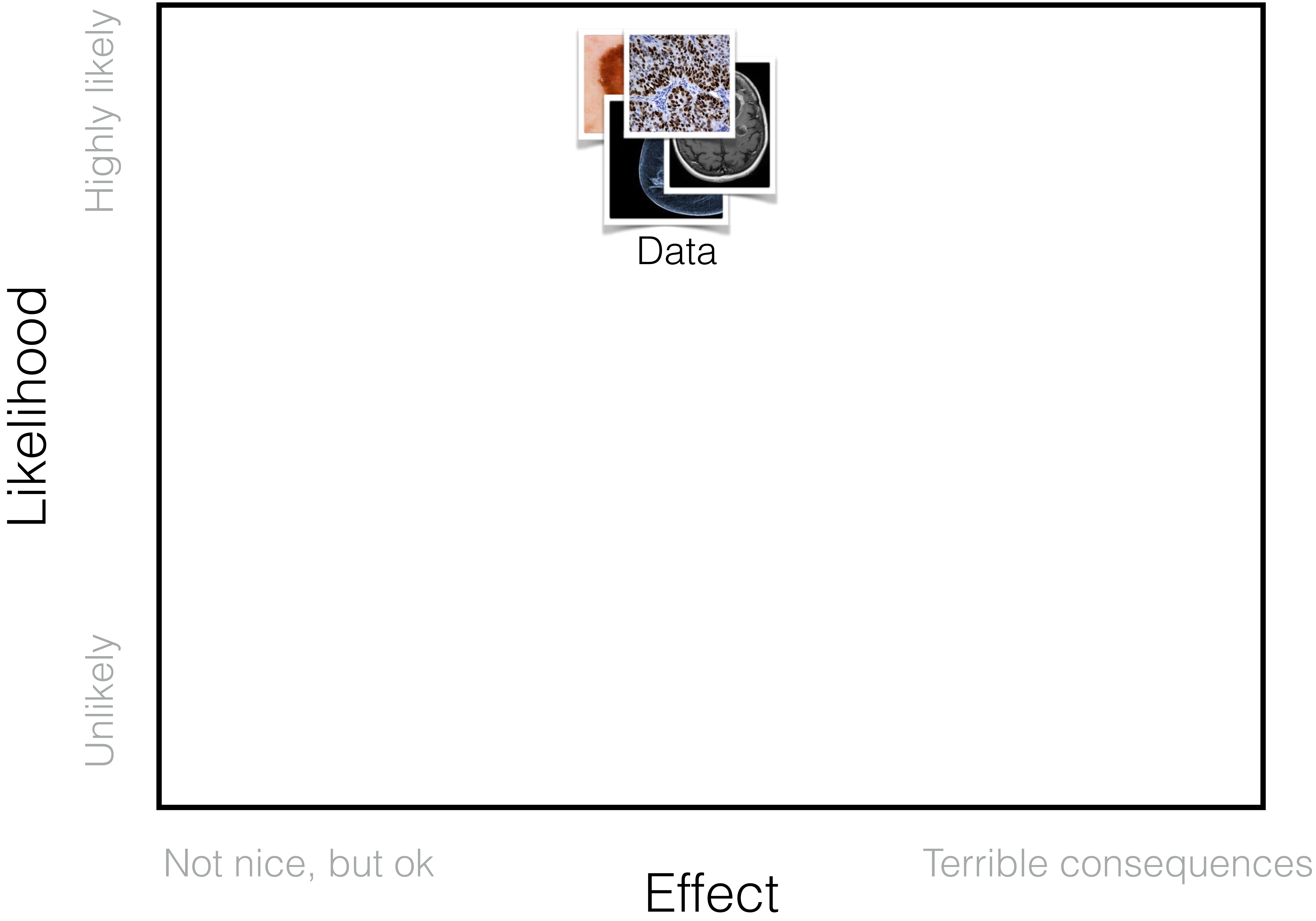
Stanford MEDICINE

Chart of possible reasons why deep learning may fail to revolutionise medicine



How doctors diagnose melanomas?

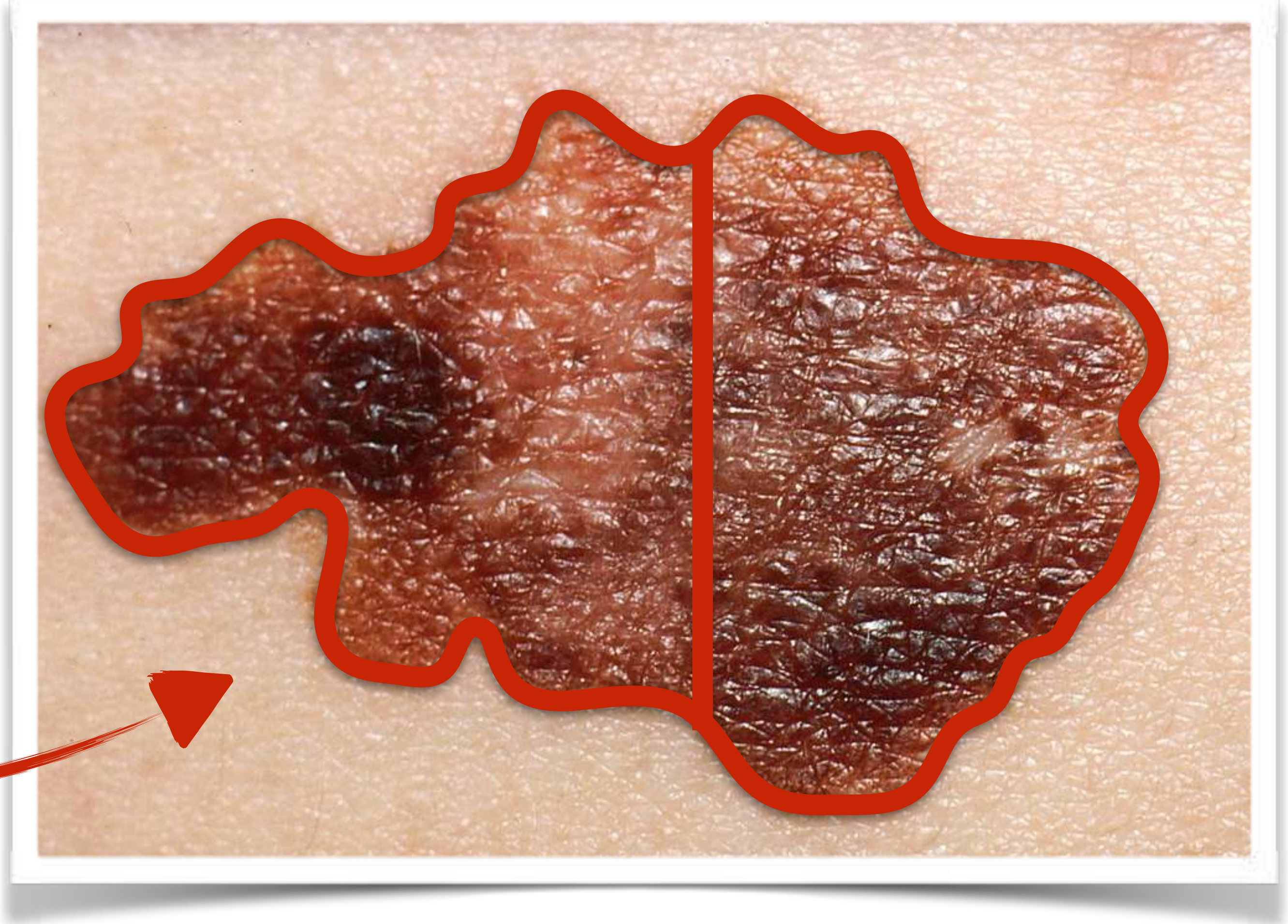
How doctors diagnose melanomas?

There is a **ABCD** rule
they learned in college

How doctors diagnose melanomas?

There is a **ABCD** rule
they learned in college

Melanomas are
Asymmetrical



How doctors diagnose melanomas?

There is a **ABCD** rule they learned in college

Melanomas are **A**symmetrical

How doctors diagnose melanomas?

There is a **ABCD** rule they learned in college

Melanomas are **A**symmetrical

Their **B**orders are uneven

How doctors diagnose melanomas?

There is a **ABCD** rule
they learned in college

Melanomas are
Asymmetrical

Their **B**orders are
uneven

How doctors diagnose melanomas?

There is a **ABCD** rule
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✓ Melanomas are **A**symmetrical

✓ Their **B**orders are uneven

Colour can be patchy and variegated

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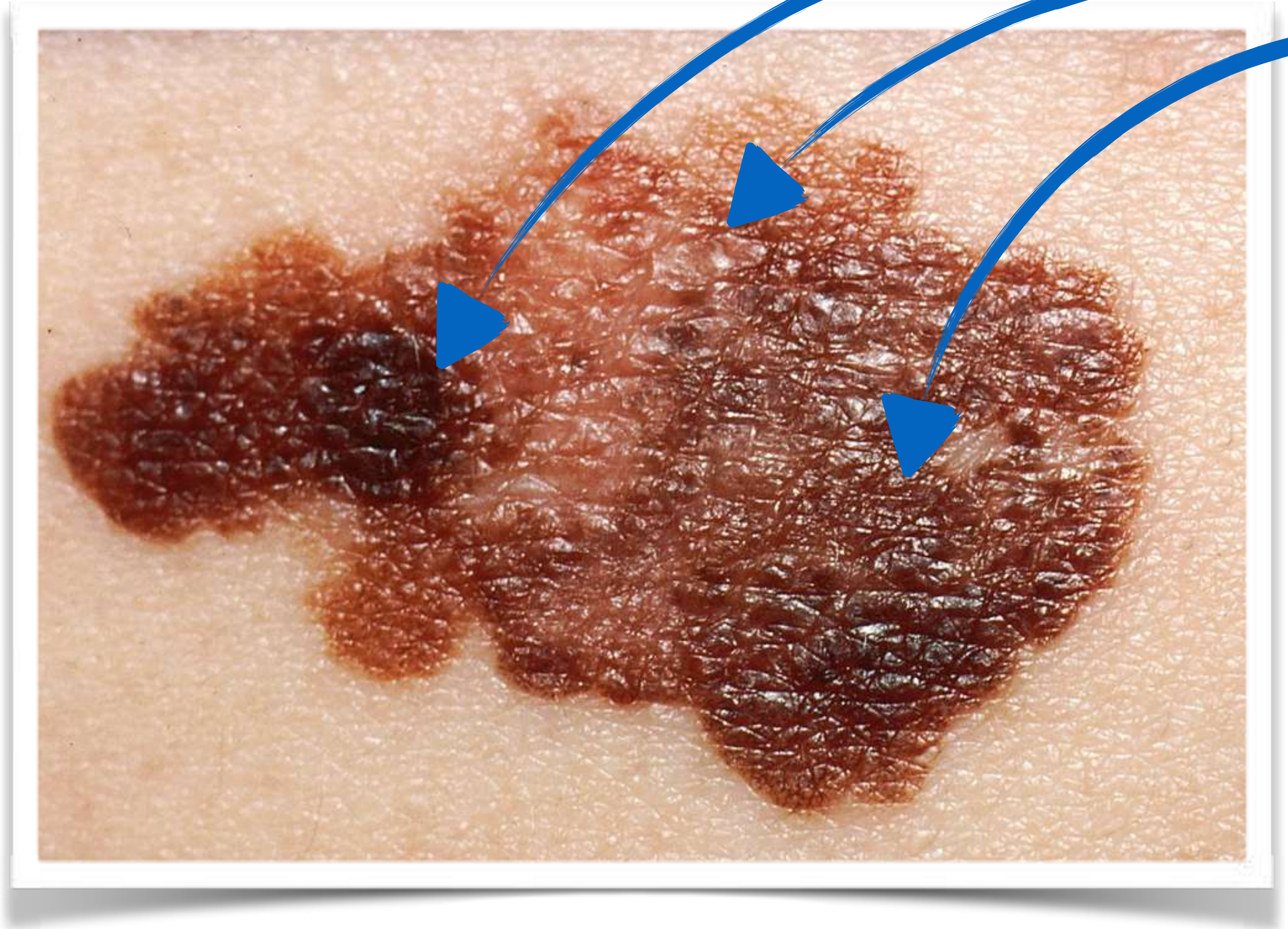

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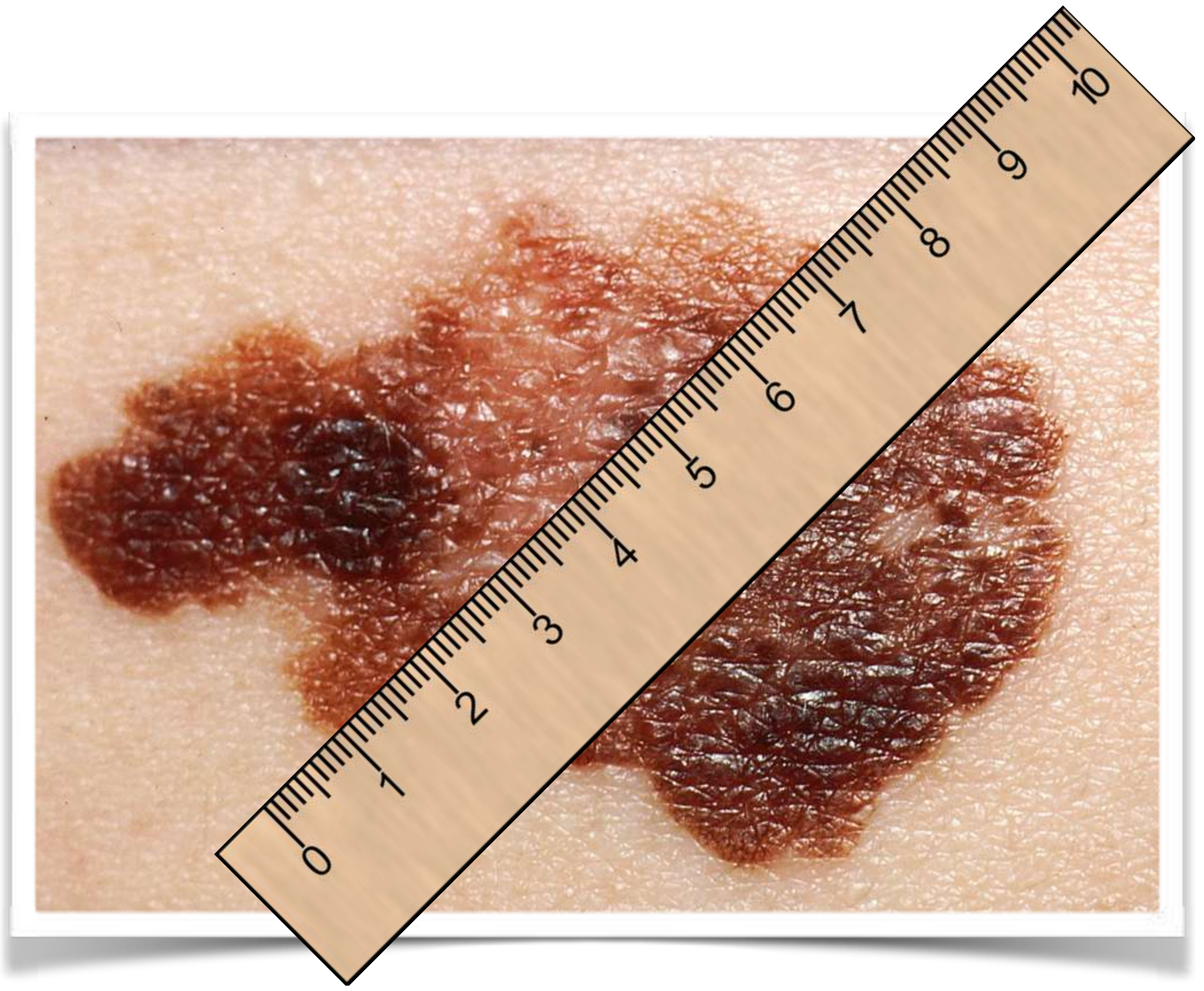

Colour can be patchy
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their **D**iameter is
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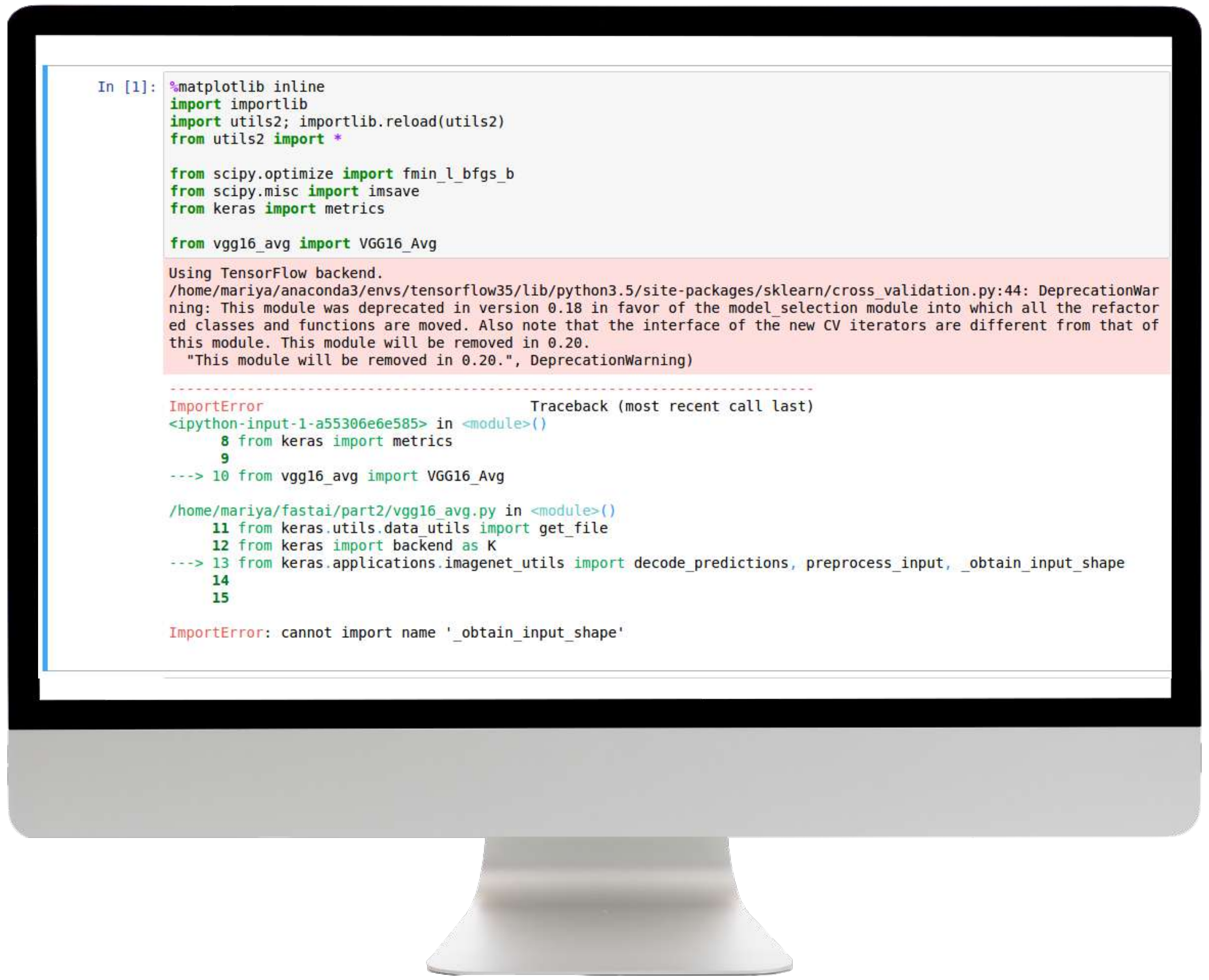
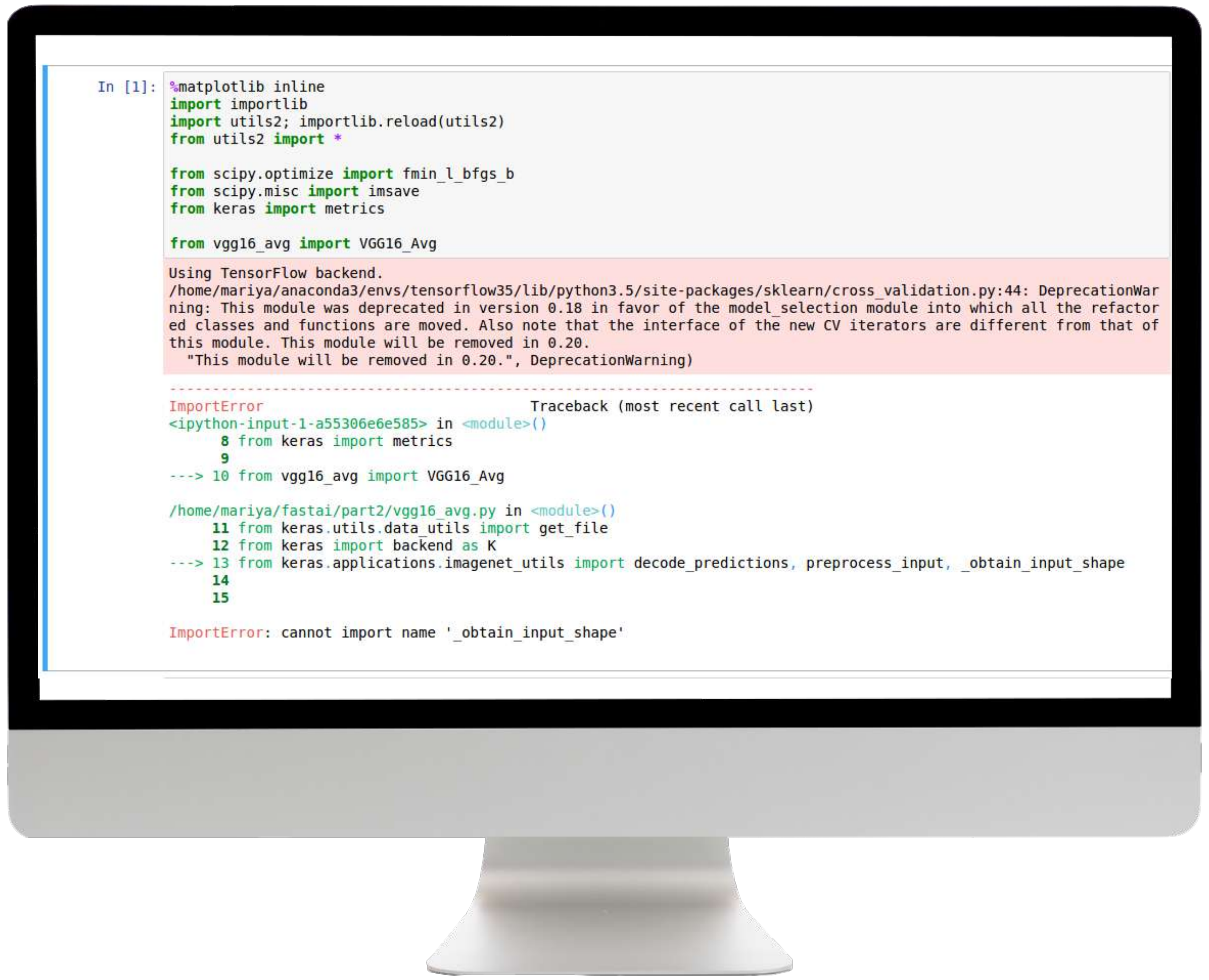
How **computers** diagnose melanomas?

How **computers** diagnose melanomas?

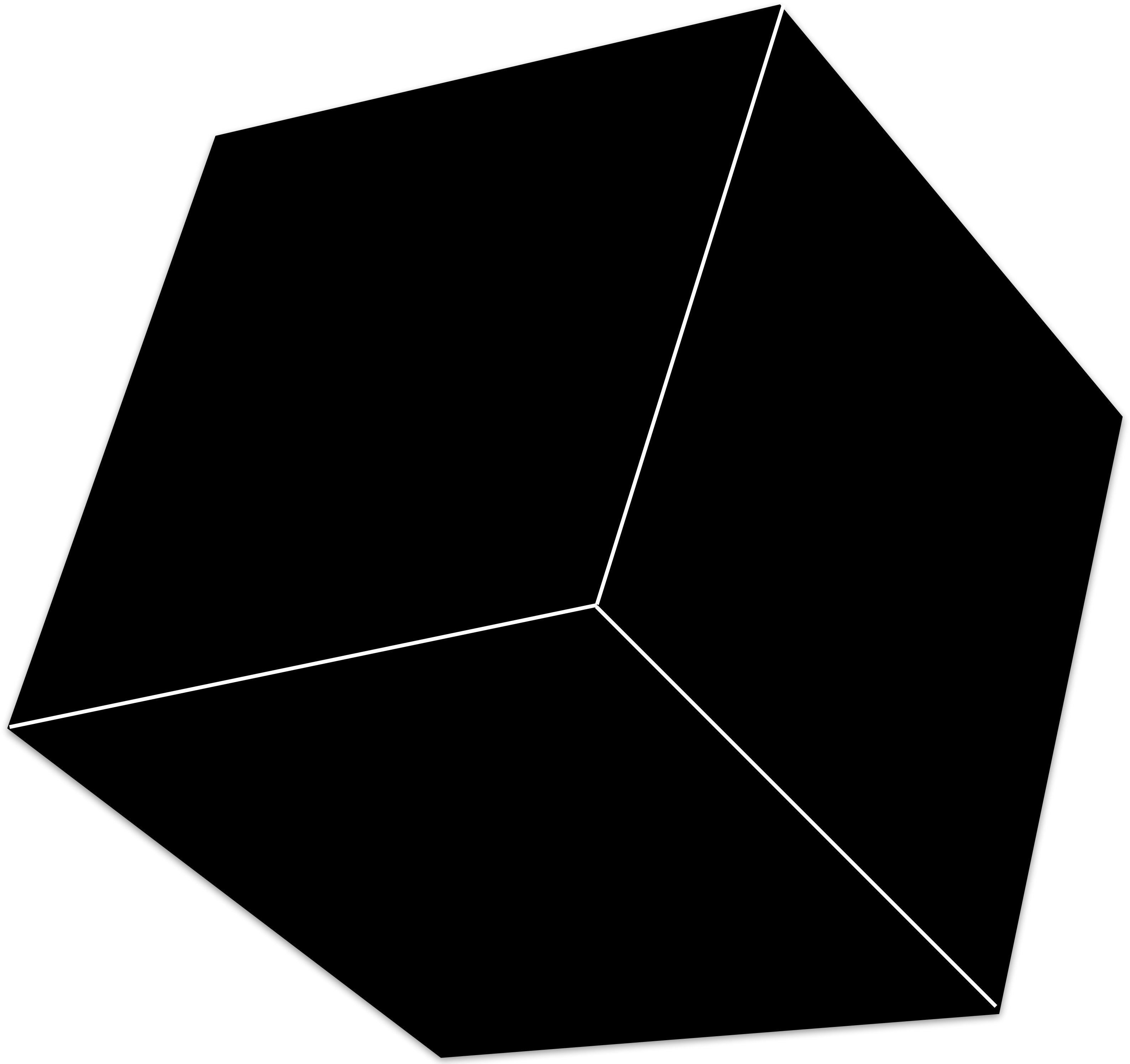


How **computers** diagnose melanomas?



Melanoma

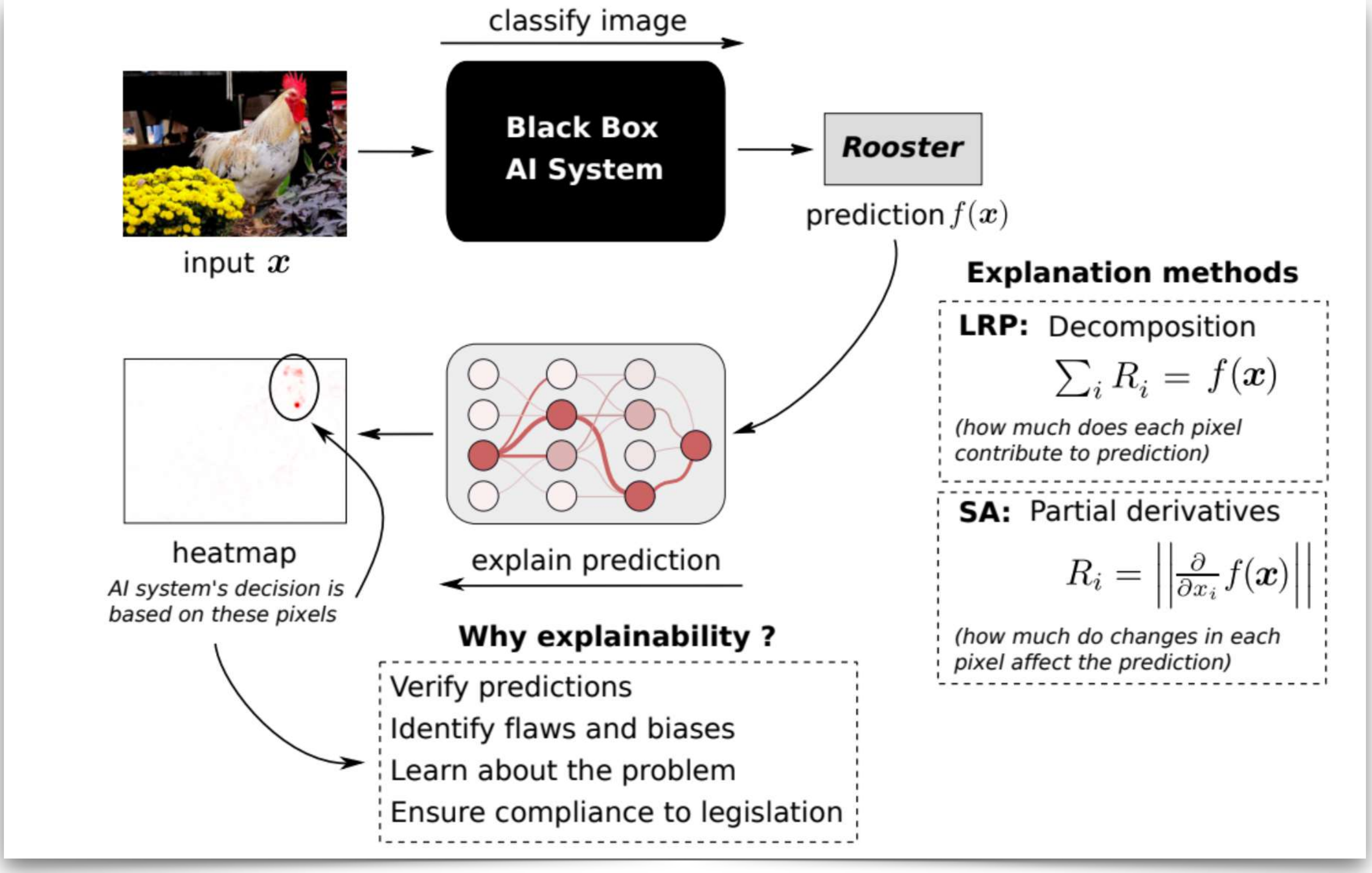
How **computers** diagnose melanomas?



Melanoma

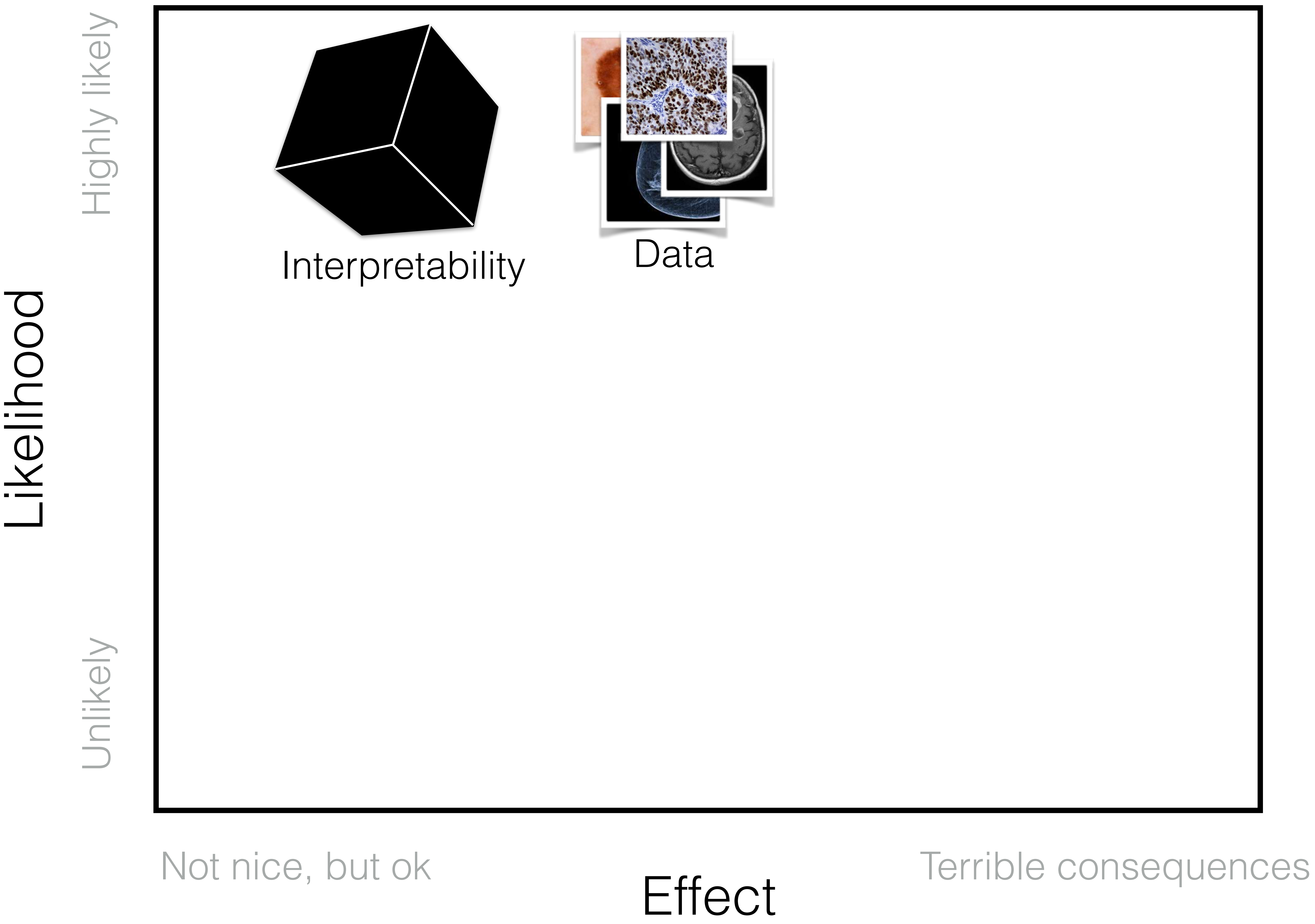
EXPLAINABLE ARTIFICIAL INTELLIGENCE: UNDERSTANDING, VISUALIZING AND INTERPRETING DEEP LEARNING MODELS

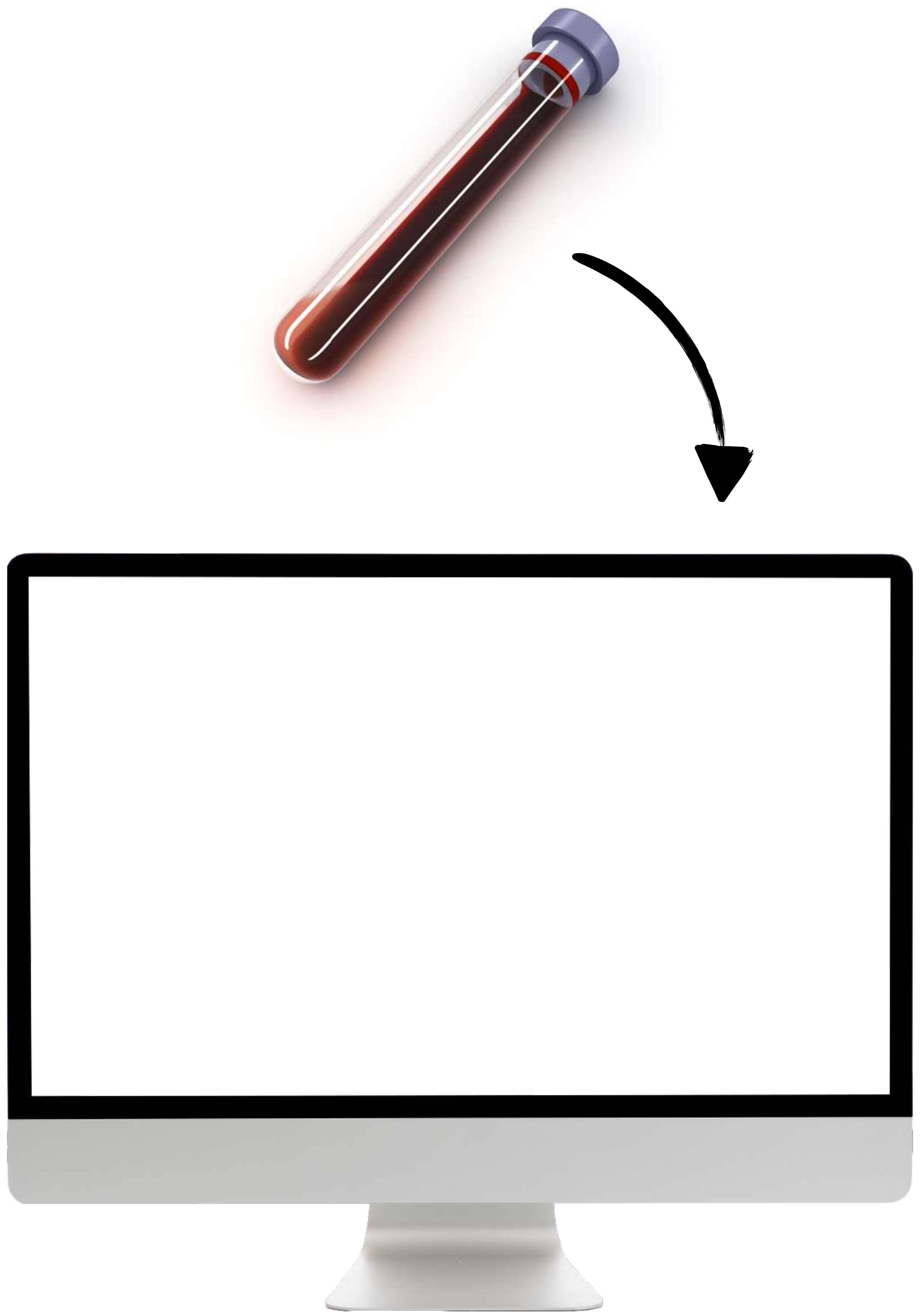
Wojciech Samek[1], *Thomas Wiegand*[1,2], *Klaus-Robert Müller*[2,3,4]



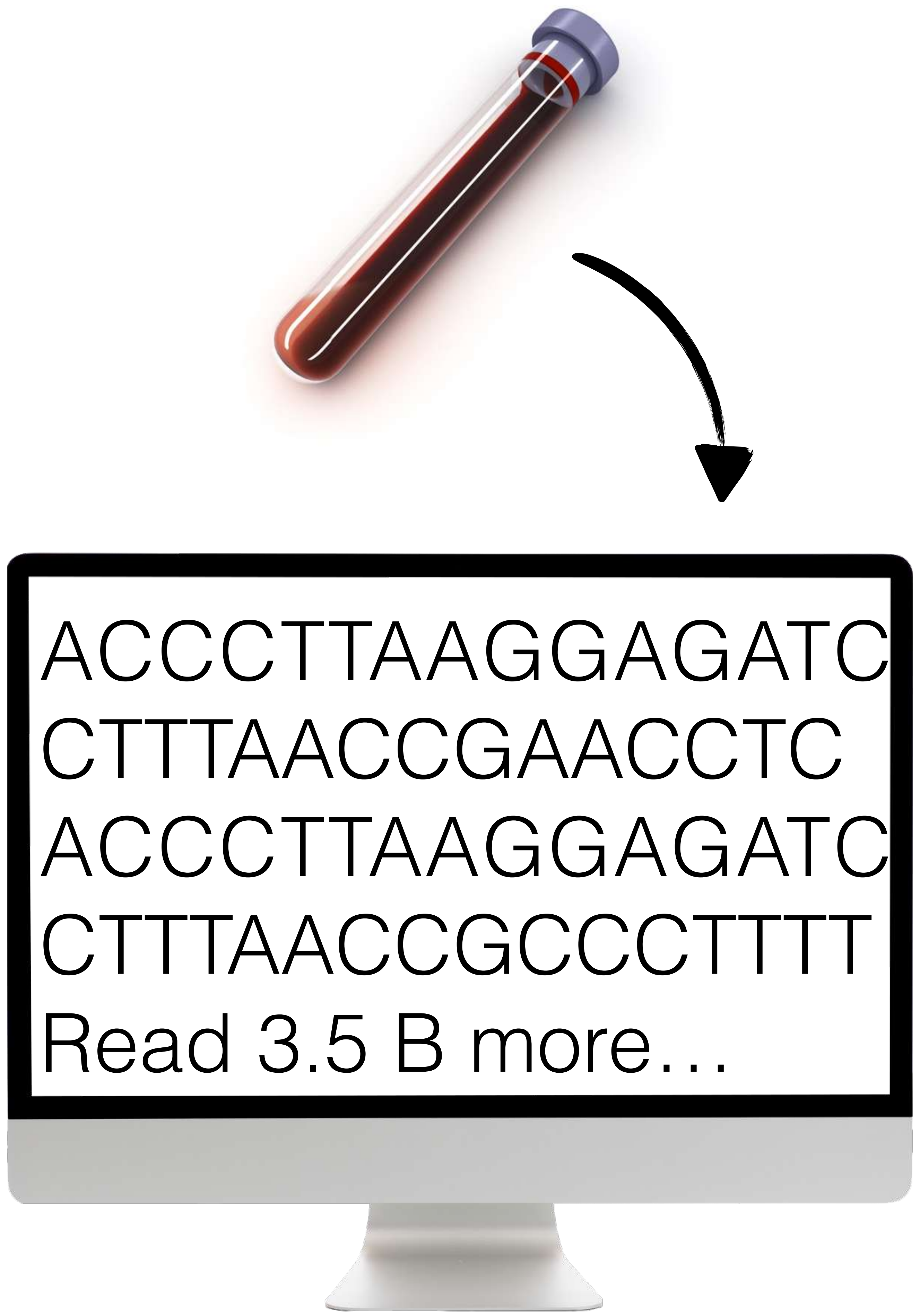
https://arxiv.org/pdf/1708.08296v1.pdf

Chart of possible reasons why deep learning may fail to revolutionise medicine





Your computer



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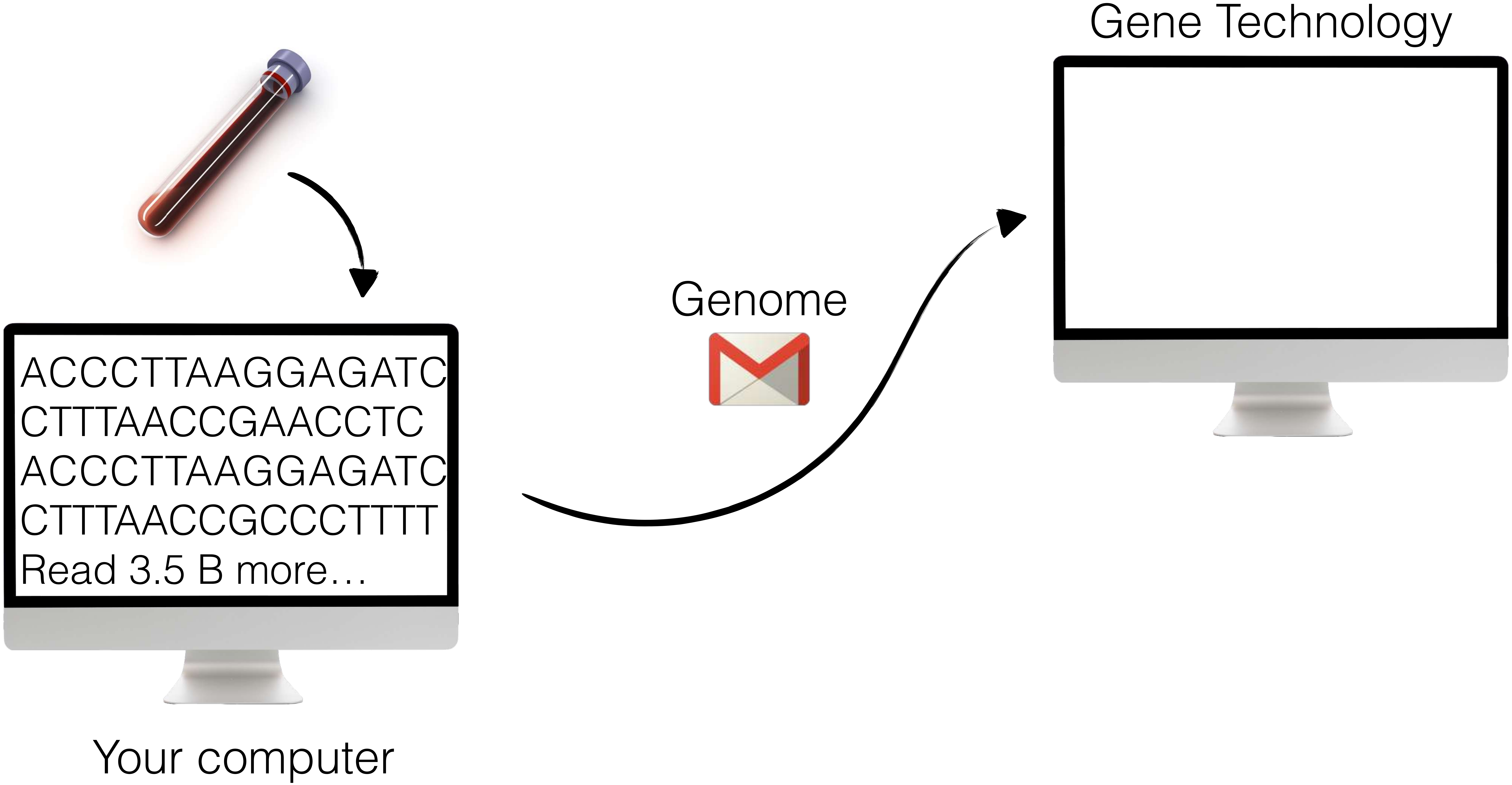
Gene Technology
ACCCTTAAGGAGATC
CTTTAACCGAACCTC
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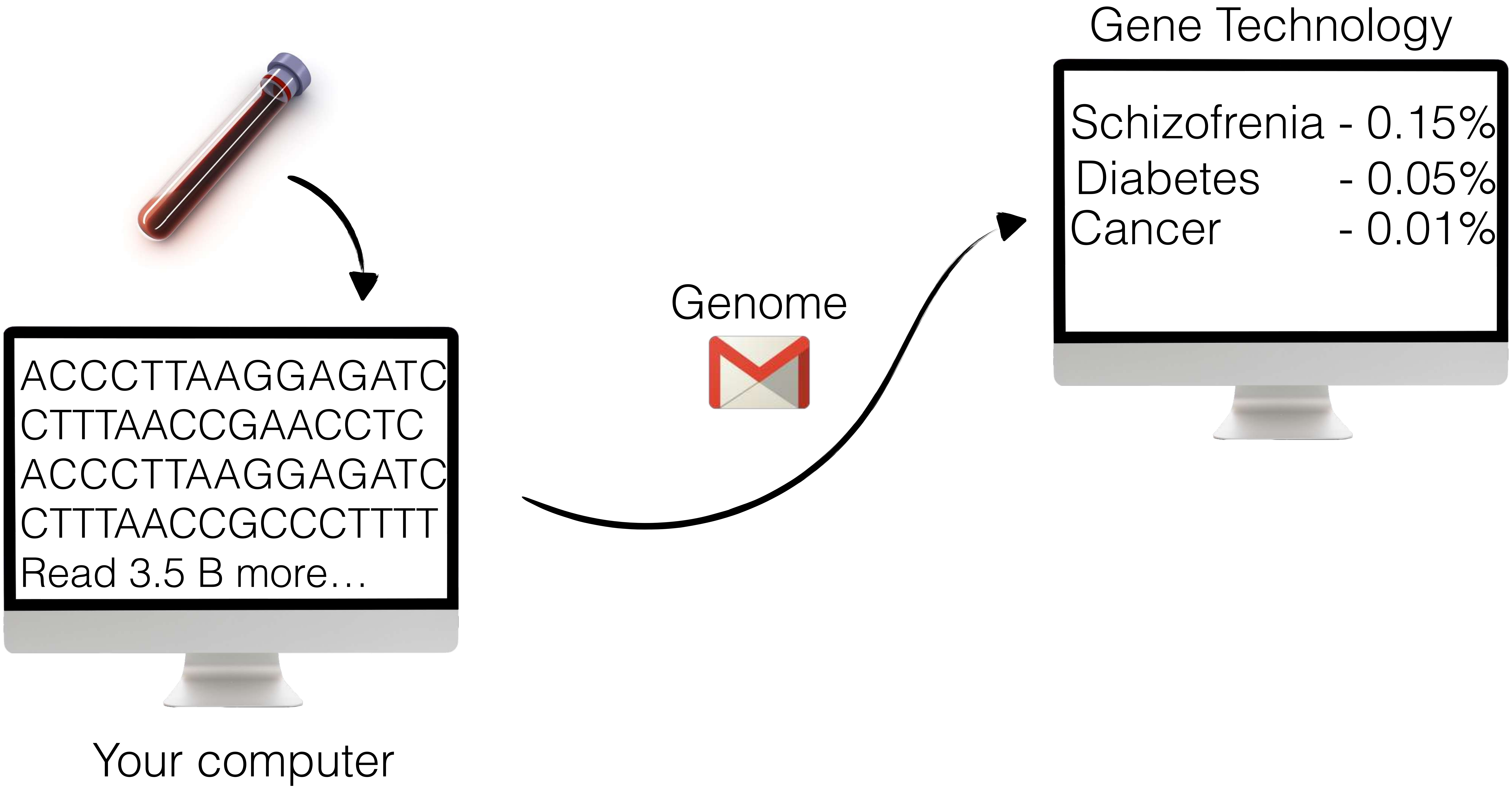
CTTTAACCGCCCTTTT
Read 3.5 B more…
Genome
Your computer


Gene Technology
Schizofrenia - 0.15%
Diabetes - 0.05%
Cancer - 0.01%
Genome
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CTTTAACCGAACCTC
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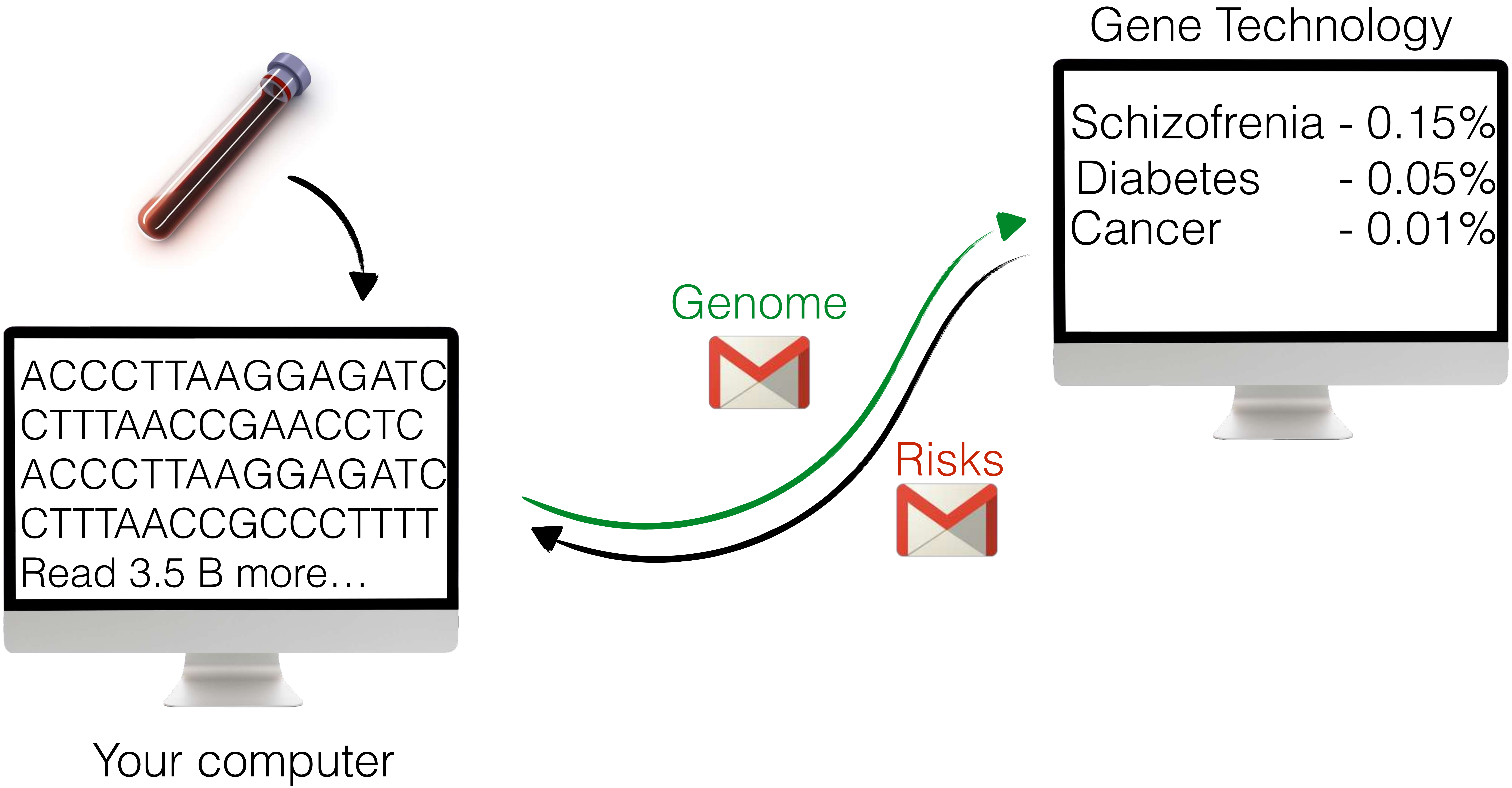
CTTTAACCGCCCTTTT
Read 3.5 B more…
Your computer


Gene Technology
Schizofrenia - 0.15%
Diabetes - 0.05%
Cancer - 0.01%
Genome
Risks
ACCCTTAAGGAGATC
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ACCCTTAAGGAGATC
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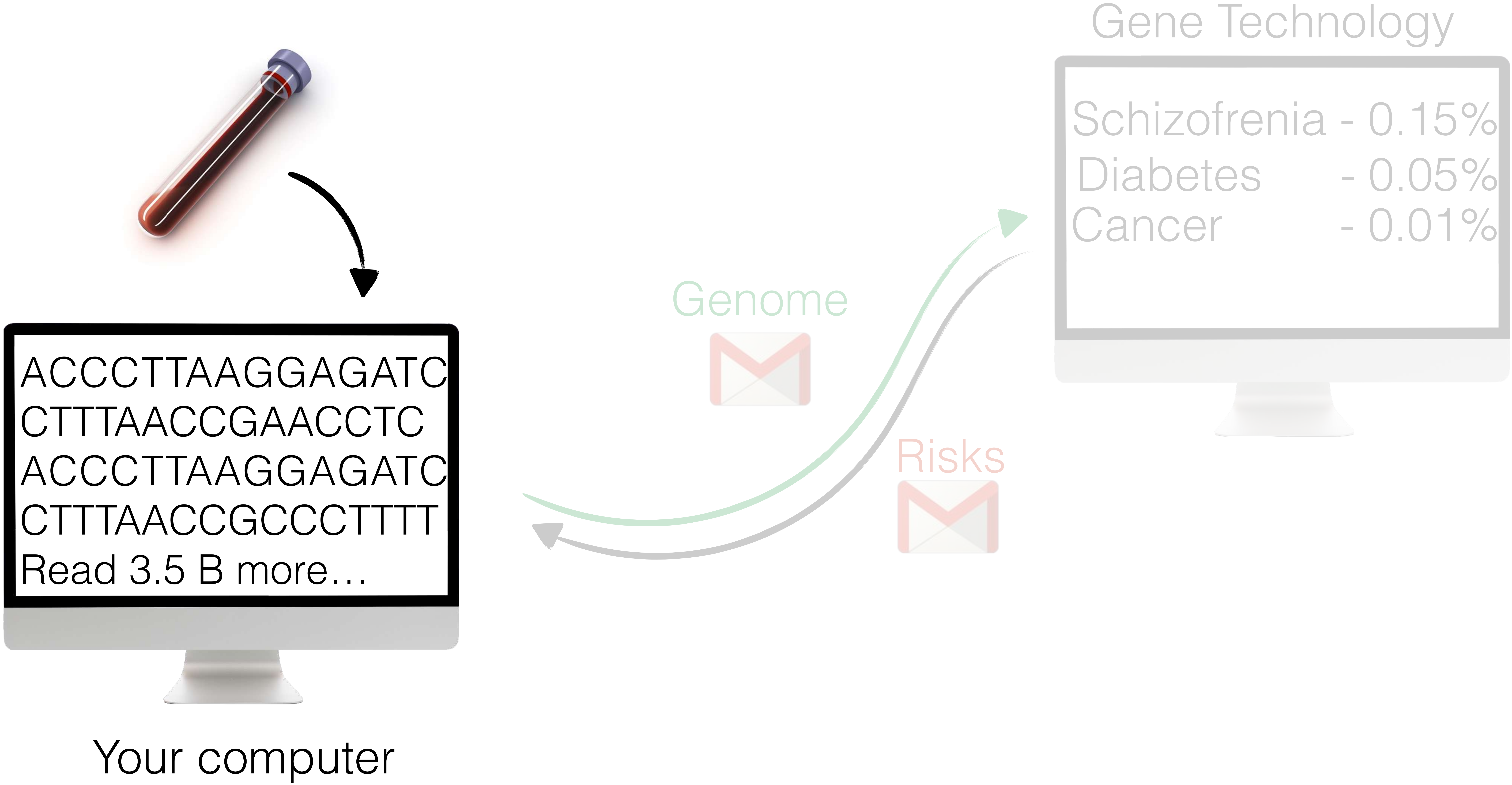
Read 3.5 B more…
Your computer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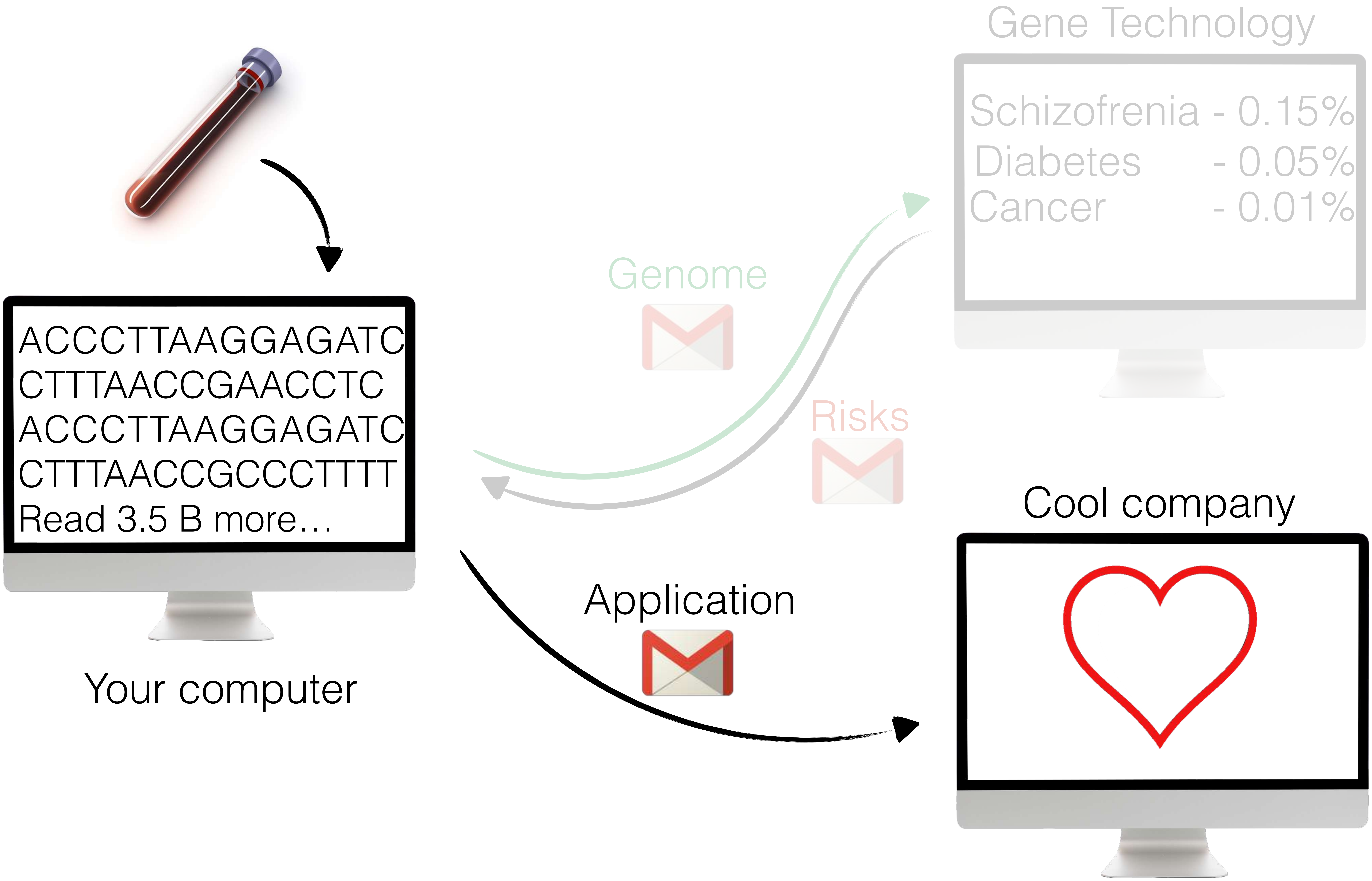
Your computer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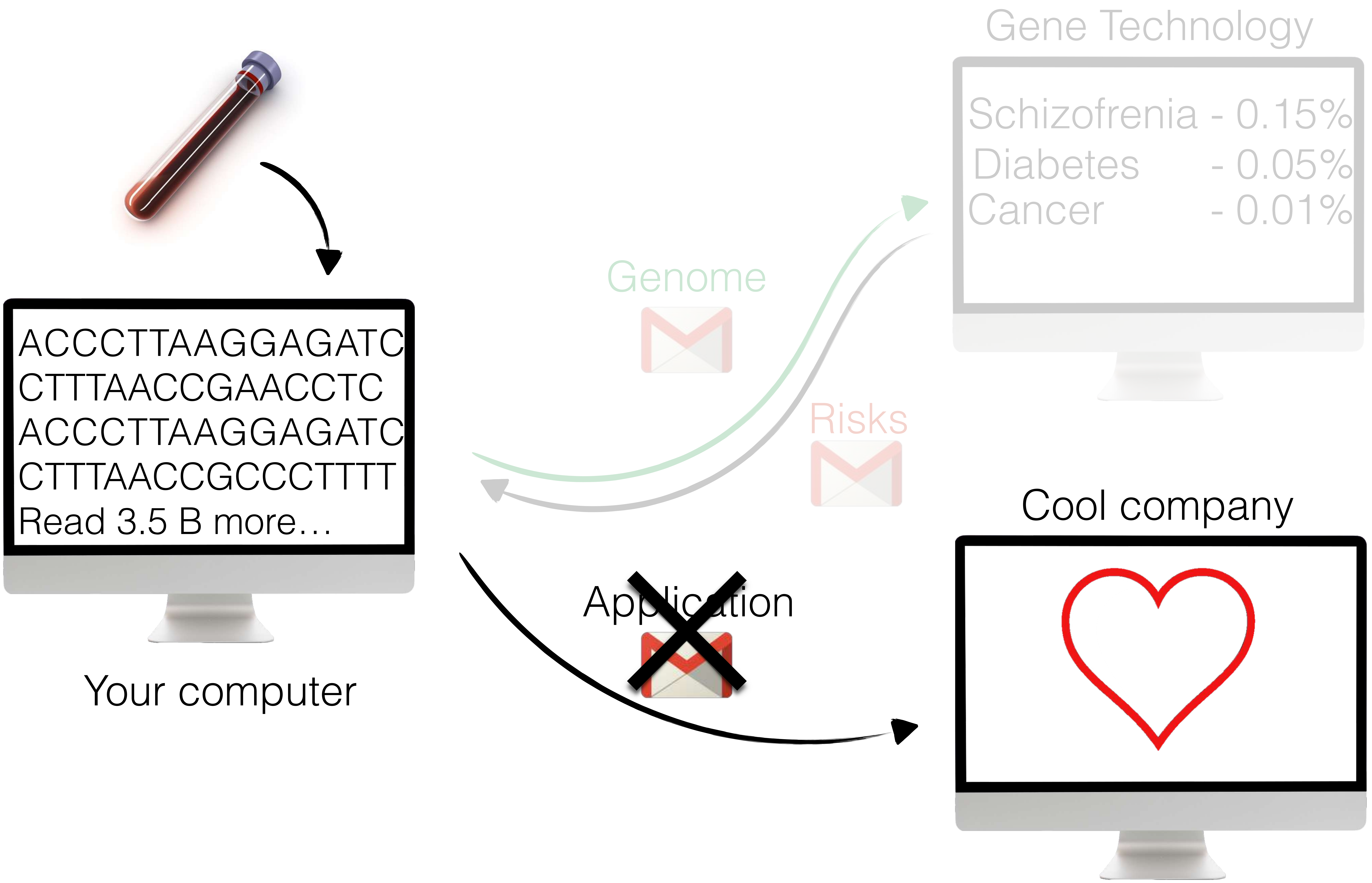
Read 3.5 B more…
Your computer
Genome
Risks
Application
Cool company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Genome
Risks
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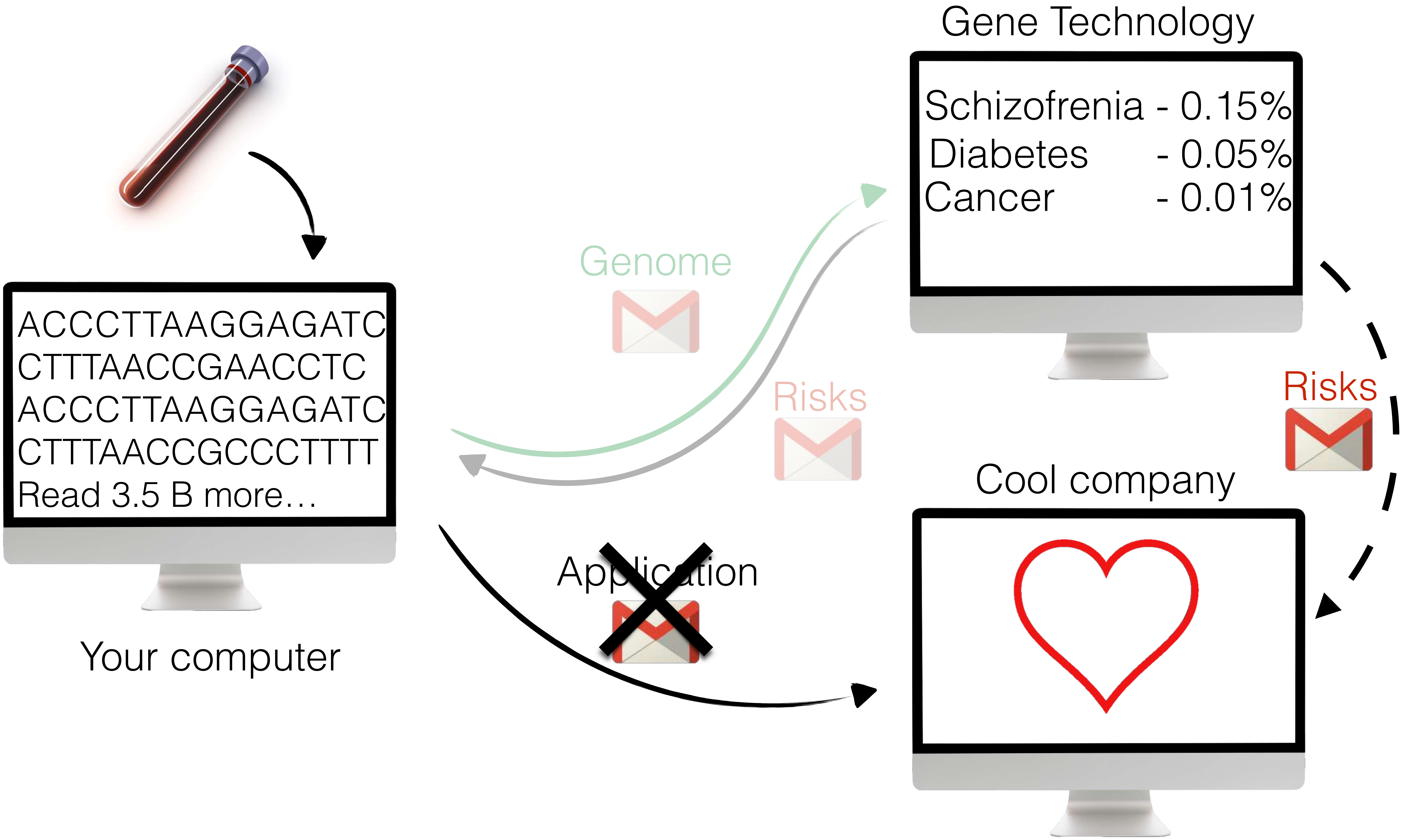
Read 3.5 B more…
Your computer
Application
Cool company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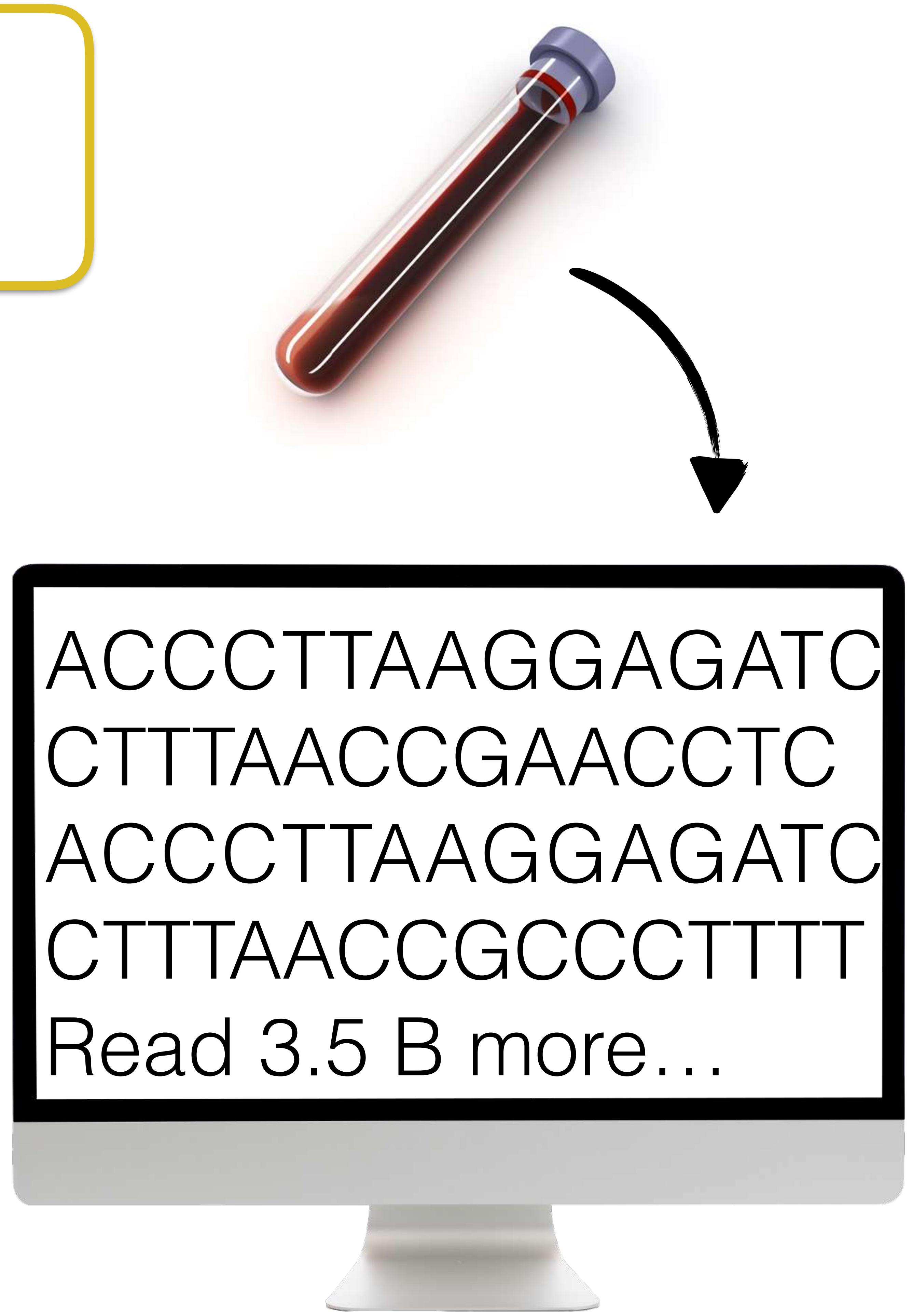
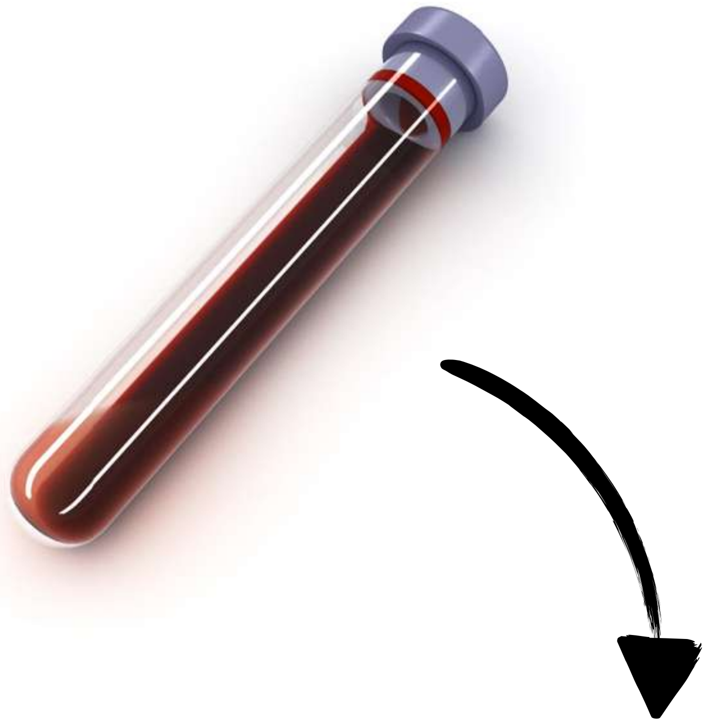
Read 3.5 B more…
Risks
Cool company
~~Application~~
Your computer

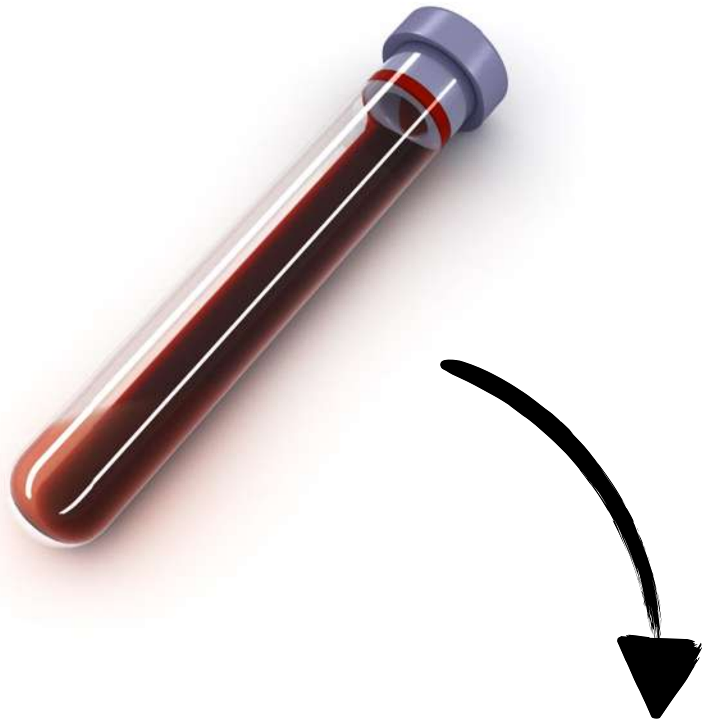


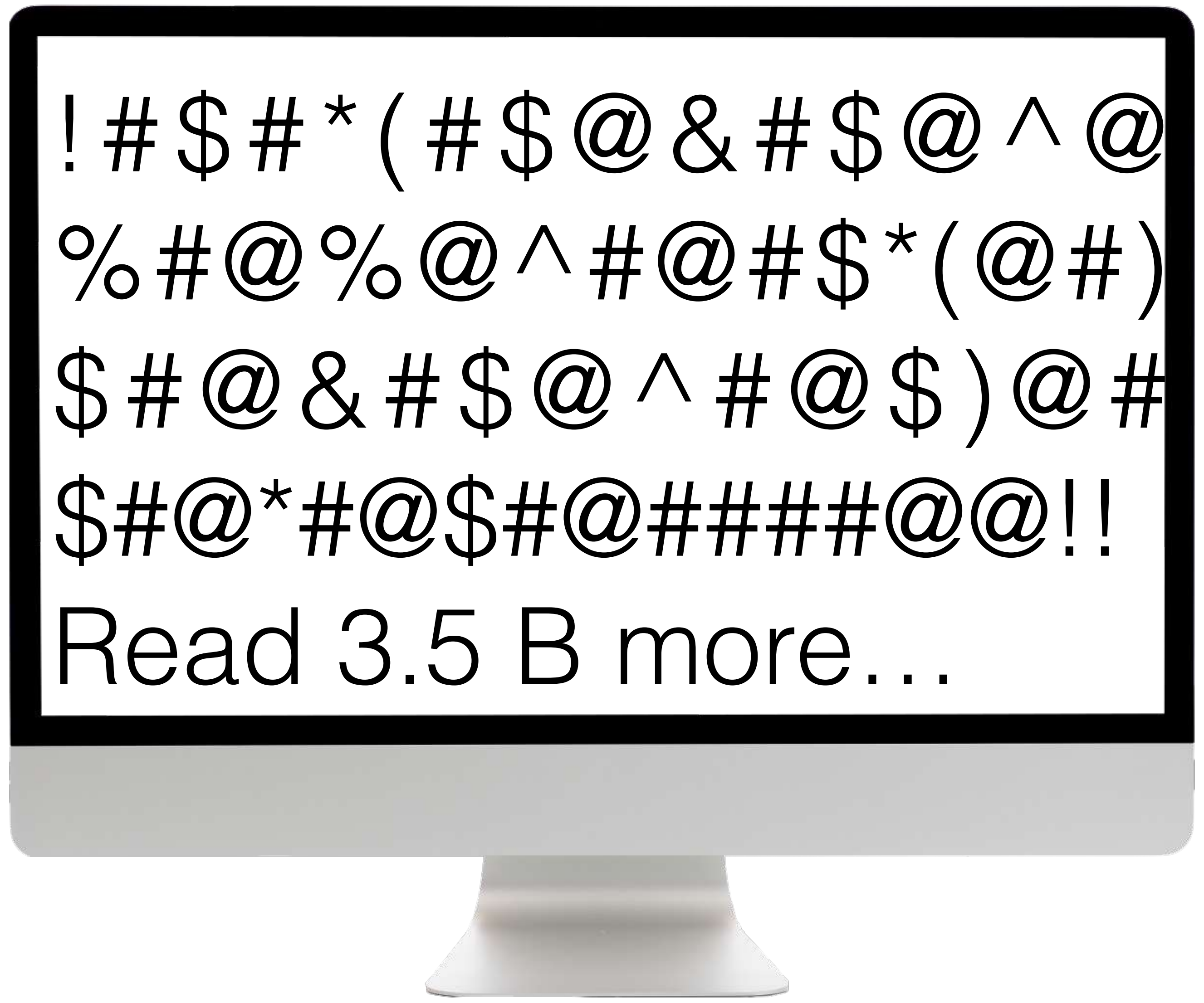
Your computer



Your computer

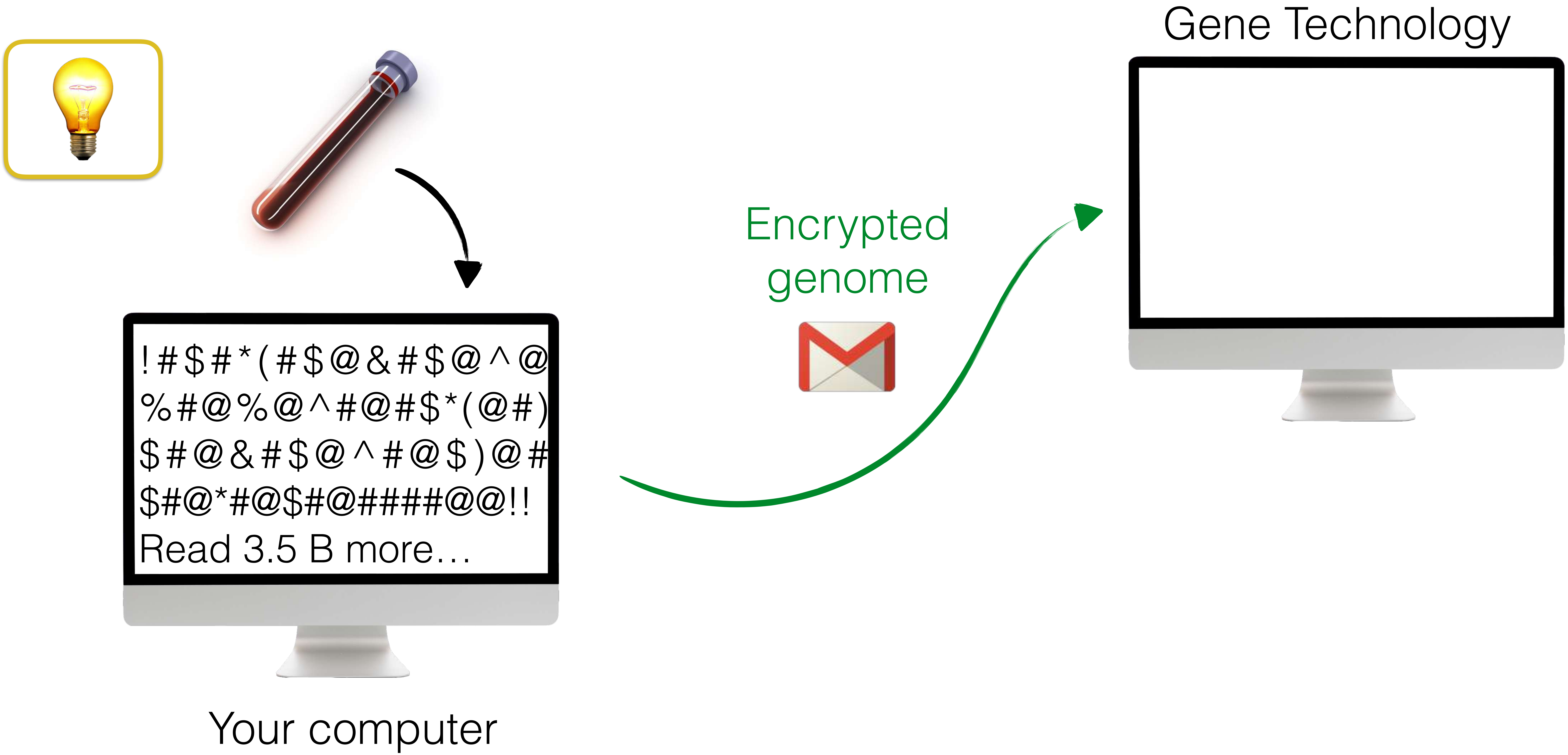
Encrypting your genome

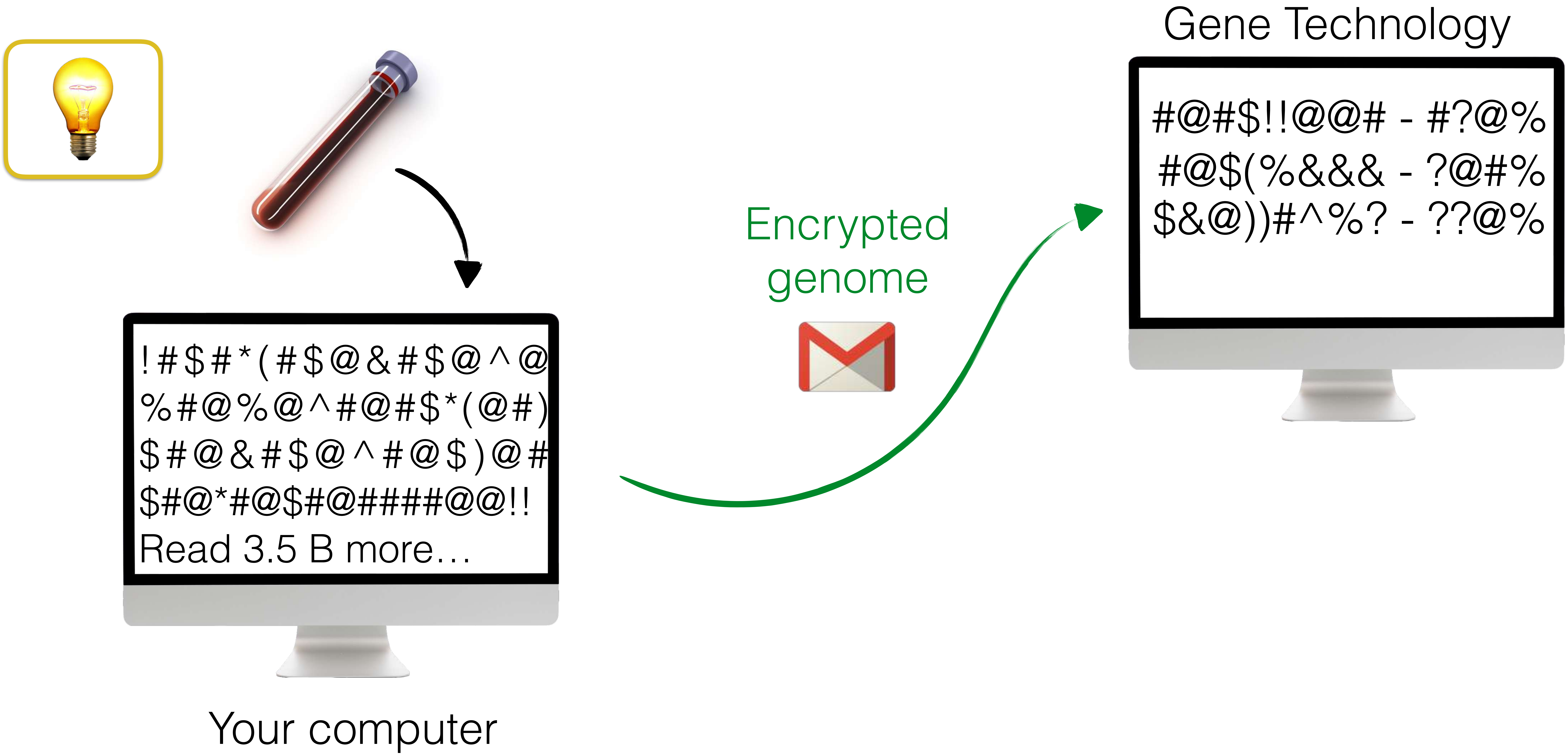


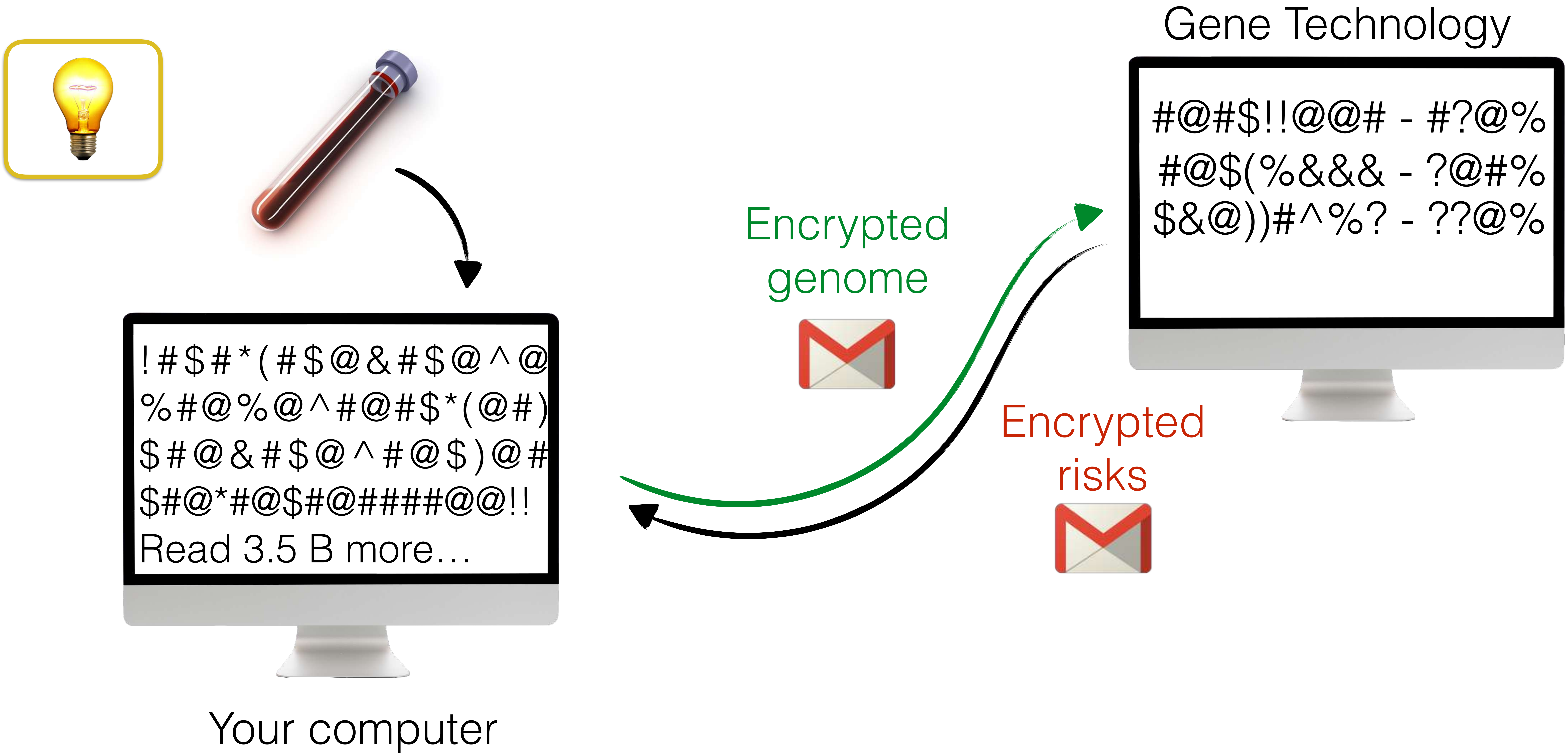


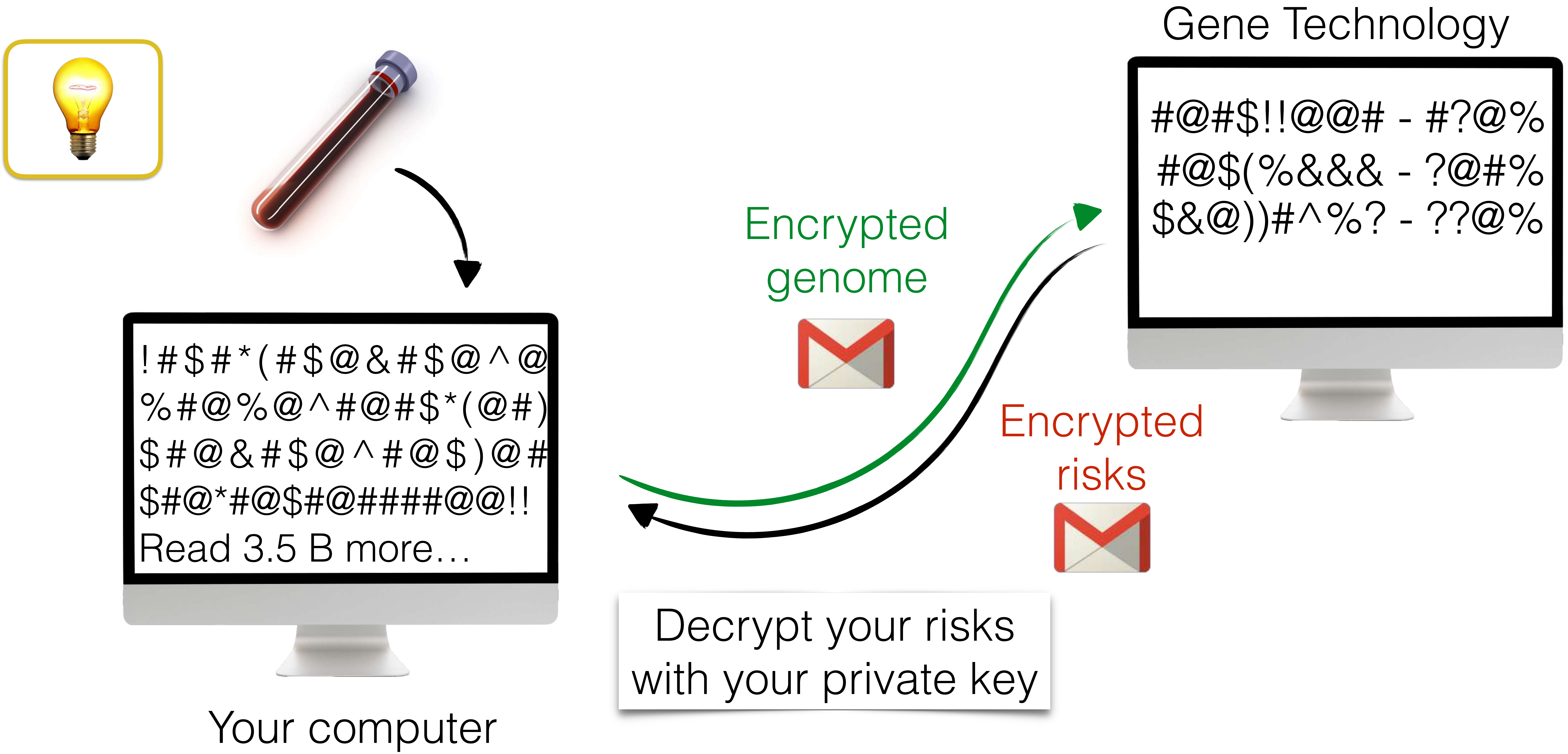
Encrypting your genome

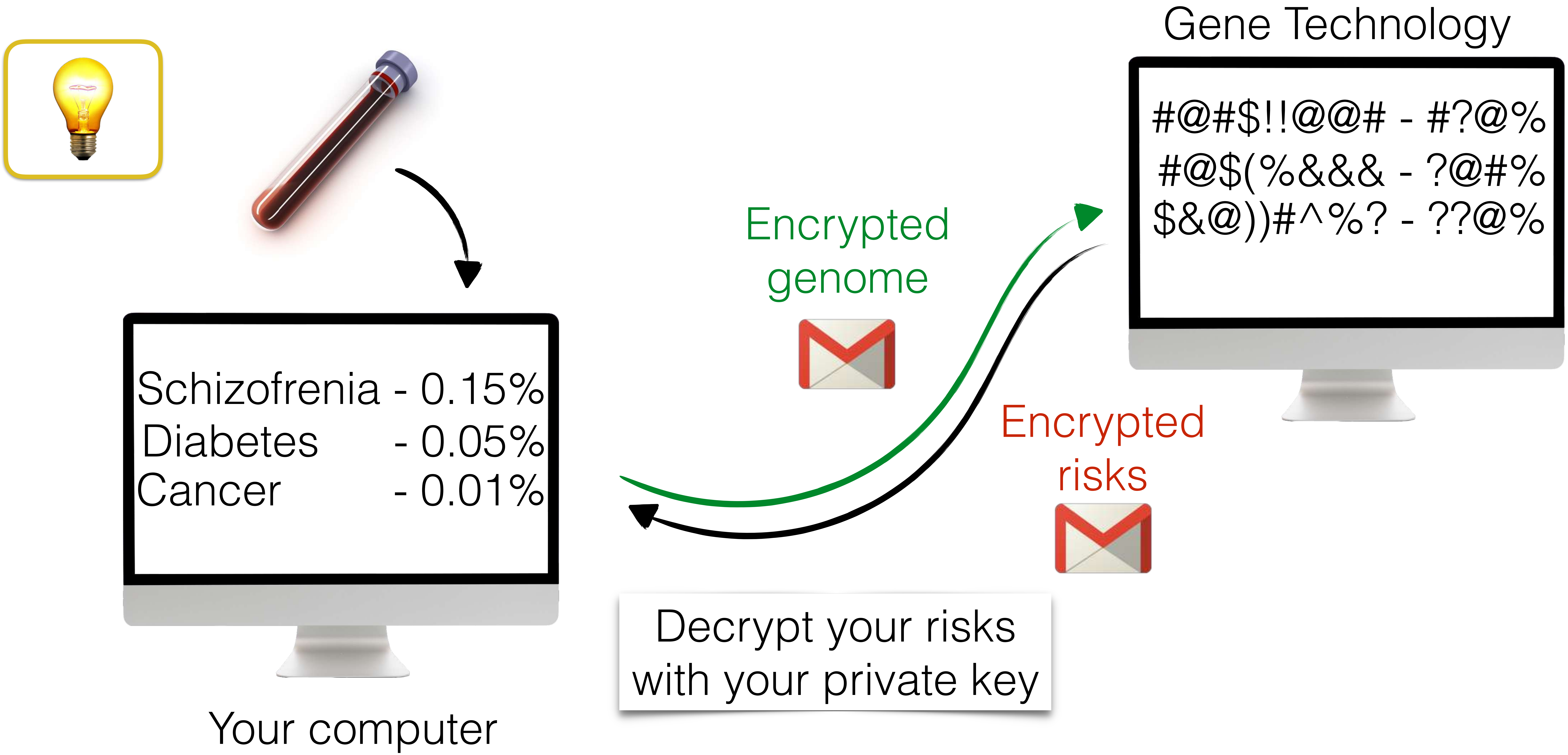
Your computer


Gene Technology
Encrypted
genome
!#$#*(#$@&#$@^@
%#@%@^#@#$*(@#)
$#@&#$@^#@$)@#
$#@*#@$#@####@@!!
Read 3.5 B more…
Your computer


Gene Technology
#@#$!!@@# - #?@%
#@$(%&&& - ?@#%
$&@))#^%? - ??@%
Encrypted genome
!#$#*(#$@&#$@^@
%#@%@^#@#$*(@#)
$#@&#$@^#@$)@#
$#@*#@$#@####@@!!
Read 3.5 B more…
Your computer


Gene Technology
#@#$!!@@# - #?@%
#@$(%&&& - ?@#%
$&@))#^%? - ??@%
Encrypted genome
Encrypted risks
!#$#*(#$@&#$@^@
%#@%@^#@#$*(@#)
$#@&#$@^#@$)@#
$#@*#@$#@####@@!!
Read 3.5 B more…
Your computer


Gene Technology
#@#$!!@@# - #?@%
#@$(%&&& - ?@#%
$&@))#^%? - ??@%
Encrypted
genome
Encrypted
risks
!#$#*(#$@&#$@^@
%#@%@^#@#$*(@#)
$#@&#$@^#@$)@#
$#@*#@$#@####@@!!
Read 3.5 B more…
Decrypt your risks
with your private key
Your computer



Gene Technology
#@#$!!@@# - #?@%
#@$(%&&& - ?@#%
$&@))#^%? - ??@%
Encrypted genome
Schizofrenia - 0.15%
Diabetes - 0.05%
Cancer - 0.01%
Encrypted risks
Decrypt your risks with your private key
Your computer

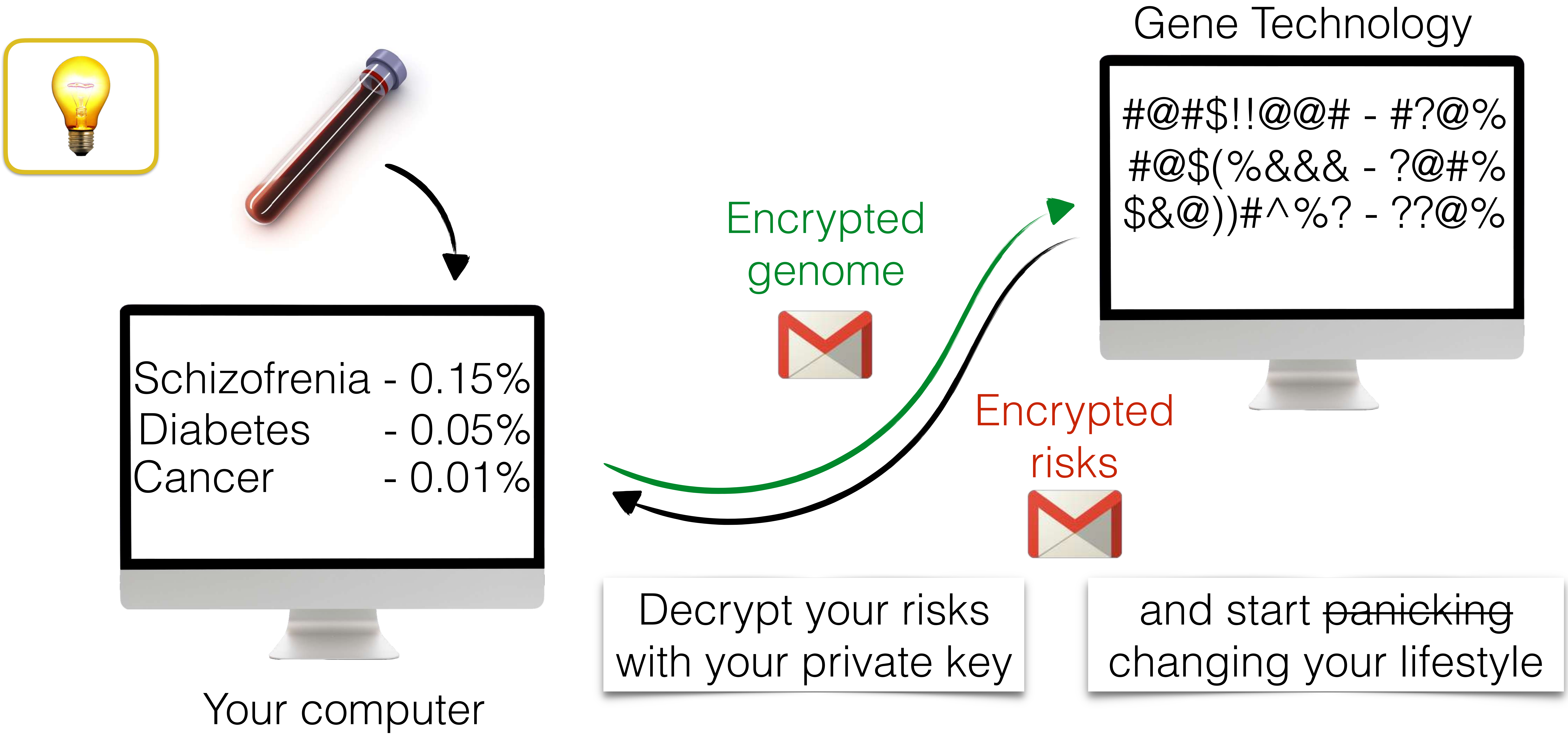
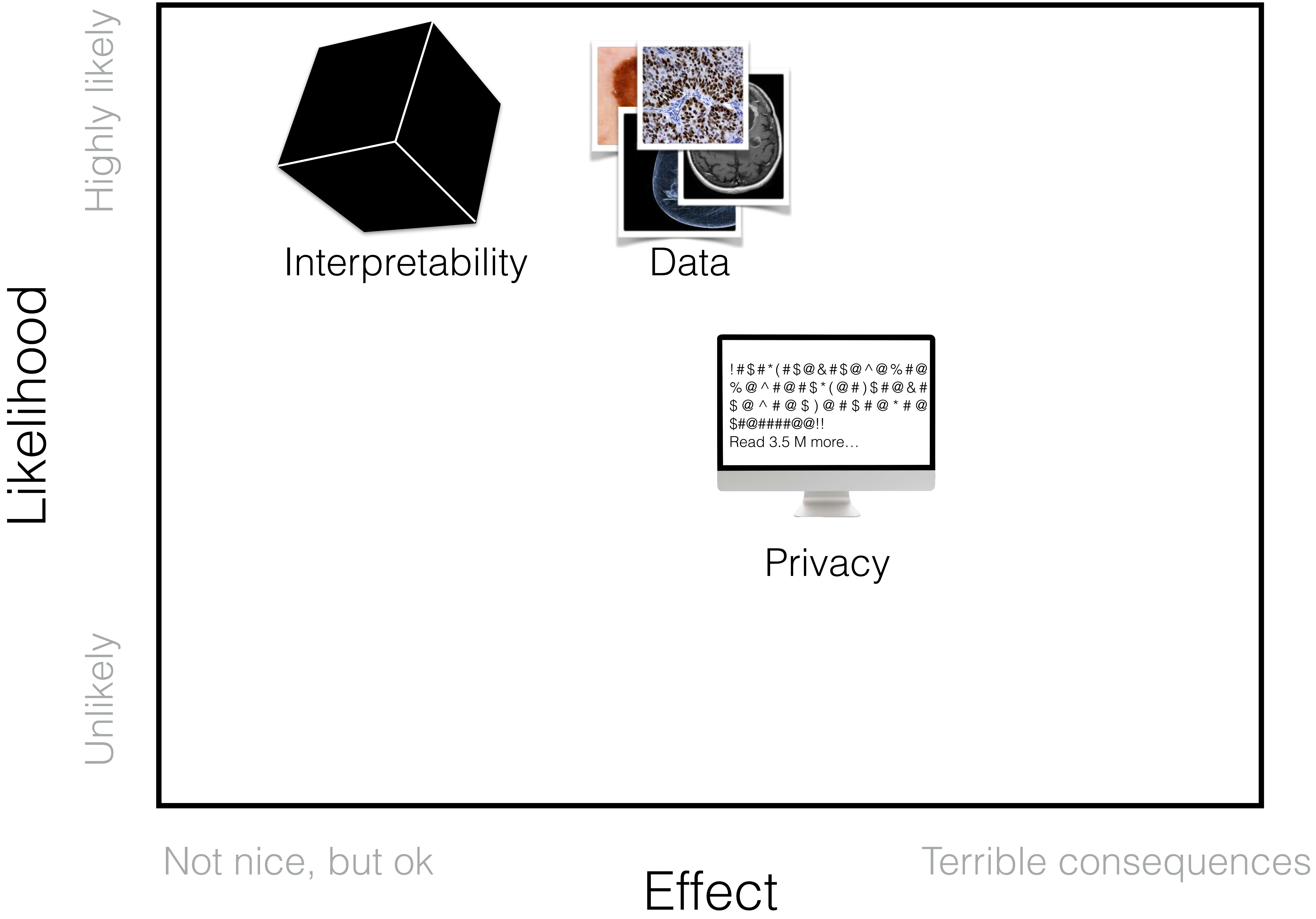

Gene Technology
#@#$!!@@# - #?@%
#@$(%&&& - ?@#%
$&@))#^%? - ??@%
Encrypted genome
Encrypted risks
Schizofrenia - 0.15%
Diabetes - 0.05%
Cancer - 0.01%
Your computer
Decrypt your risks with your private key
and start ~~panicking~~ changing your lifestyle

Chart of possible reasons why deep learning may fail to revolutionise medicine



Original image

Original image

Segmentation

Correct segmentation

Original image

Segmentation

Correct segmentation

Trees

Cars

Road

Original image

Segmentation

Correct segmentation

Trees

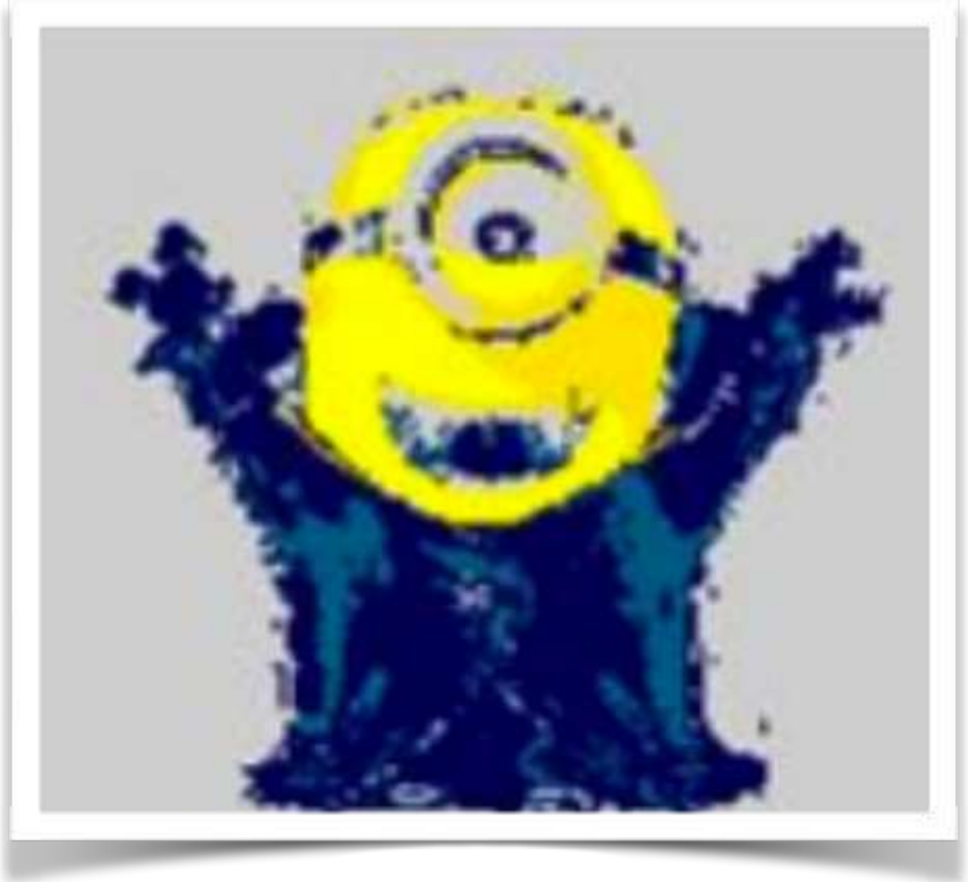
Cars

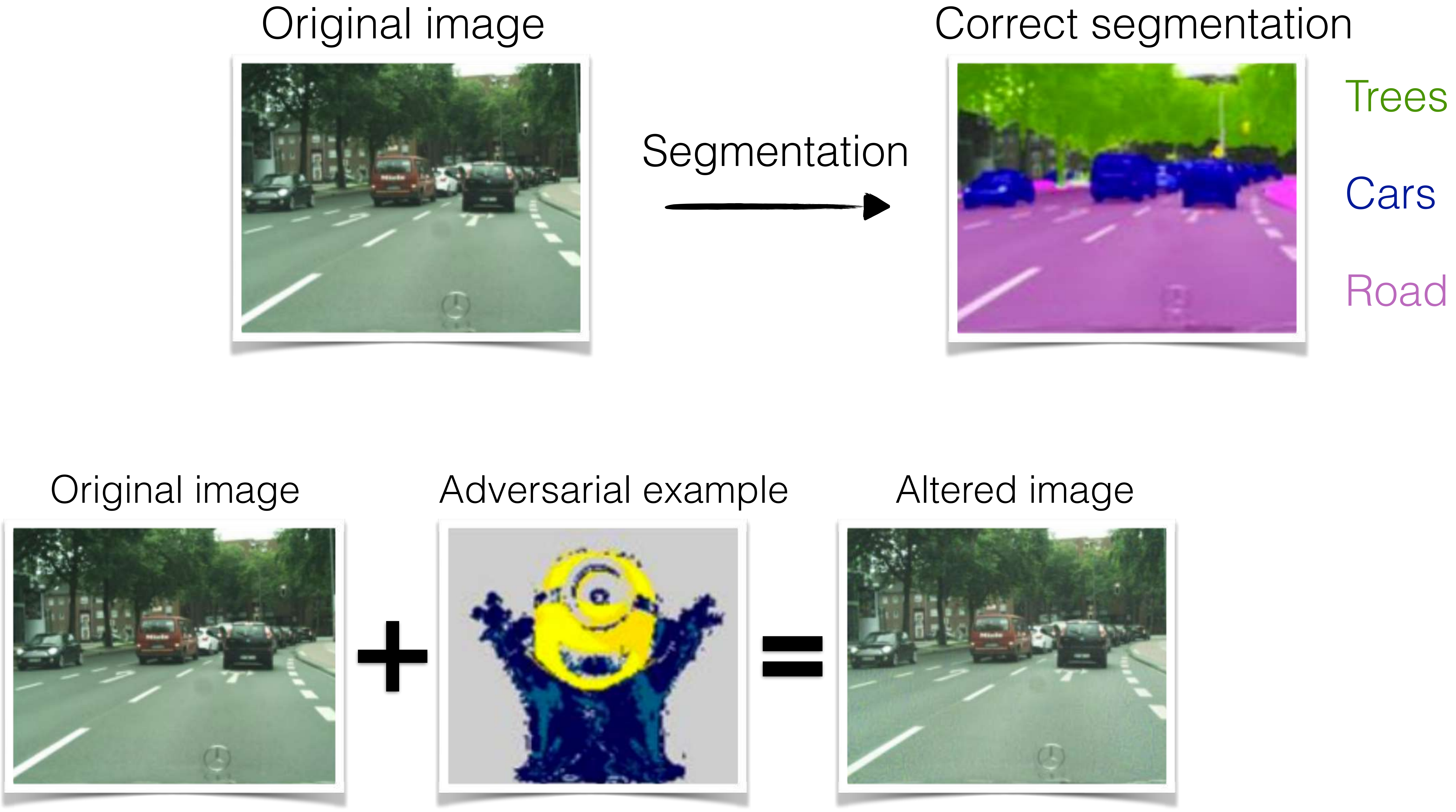
Road

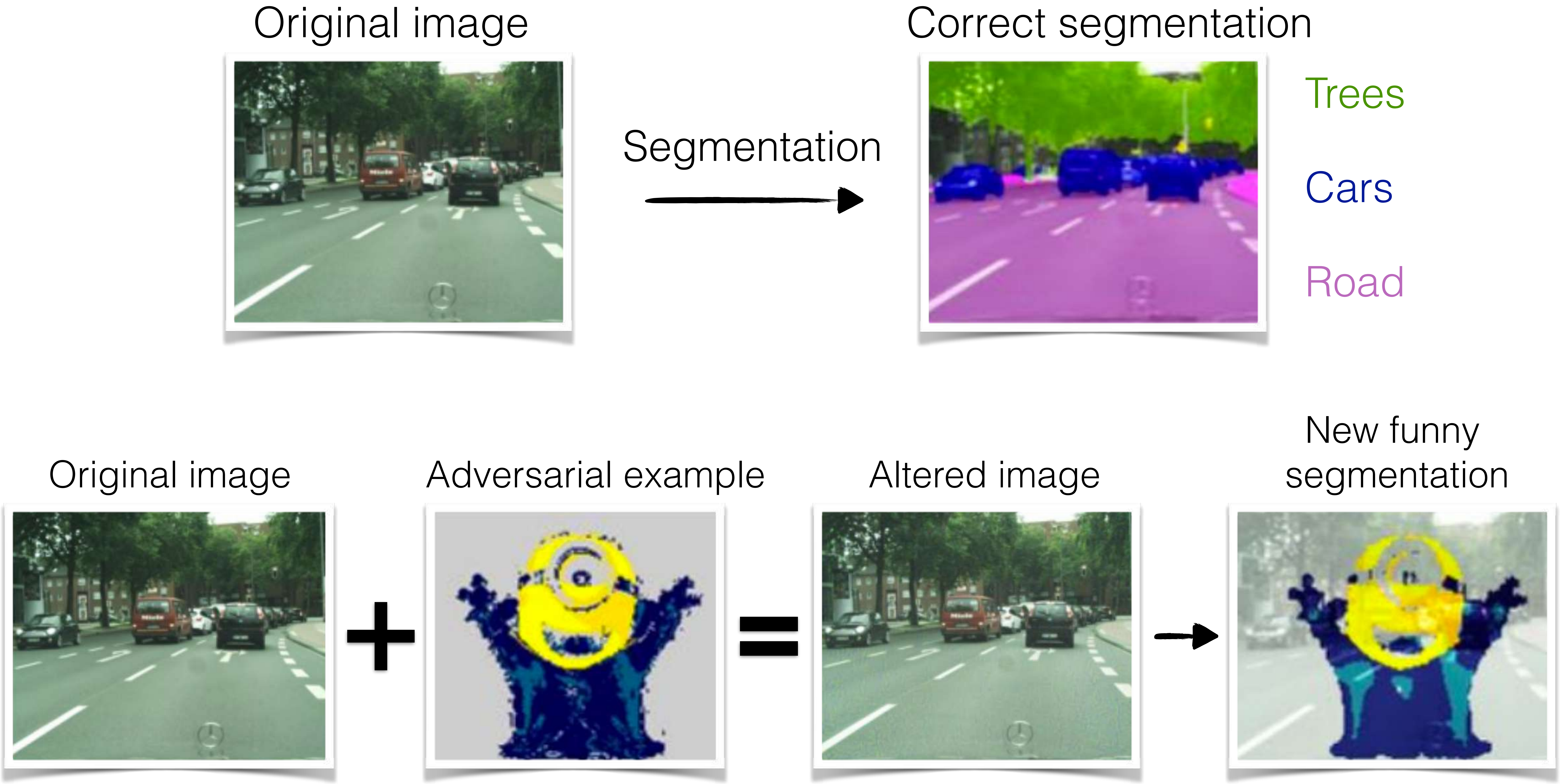
Original image

+

Adversarial example




Original image
Segmentation
Correct segmentation
Trees
Cars
Road
Original image
Adversarial example
Altered image


Original image
Segmentation
Correct segmentation
Trees
Cars
Road
Original image
Adversarial example
Altered image
New funny
segmentation


stryker
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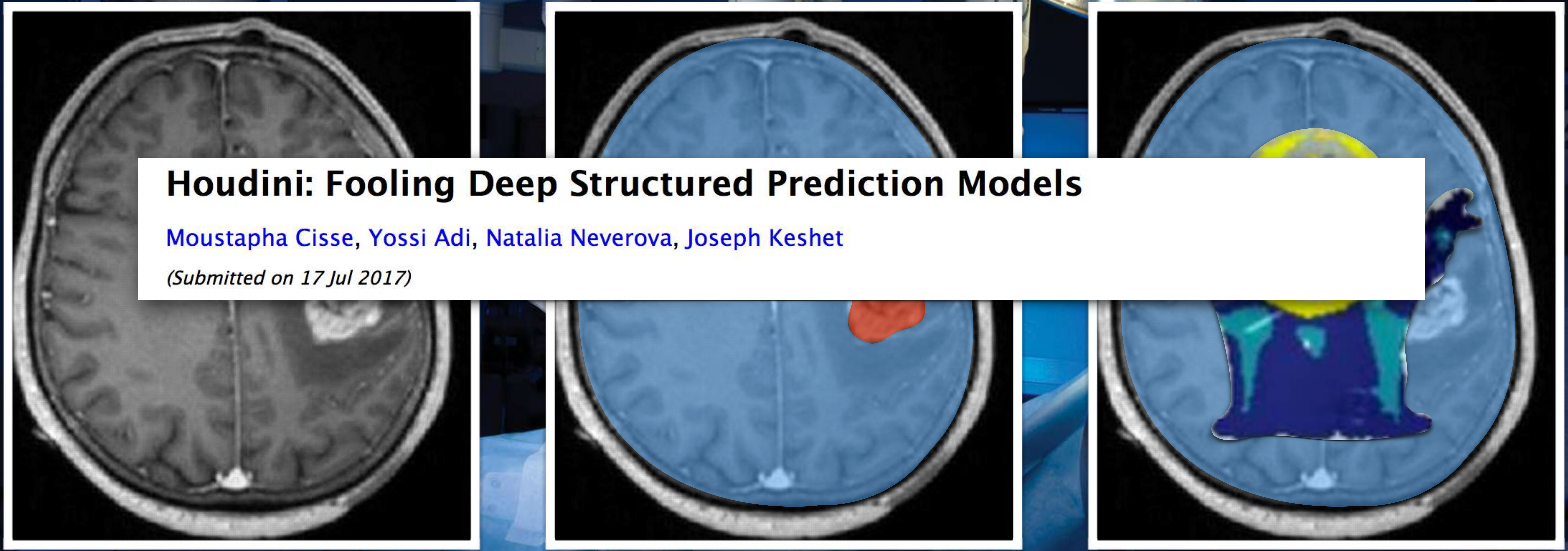
1
3


stryker
2
1


stryker


stryker

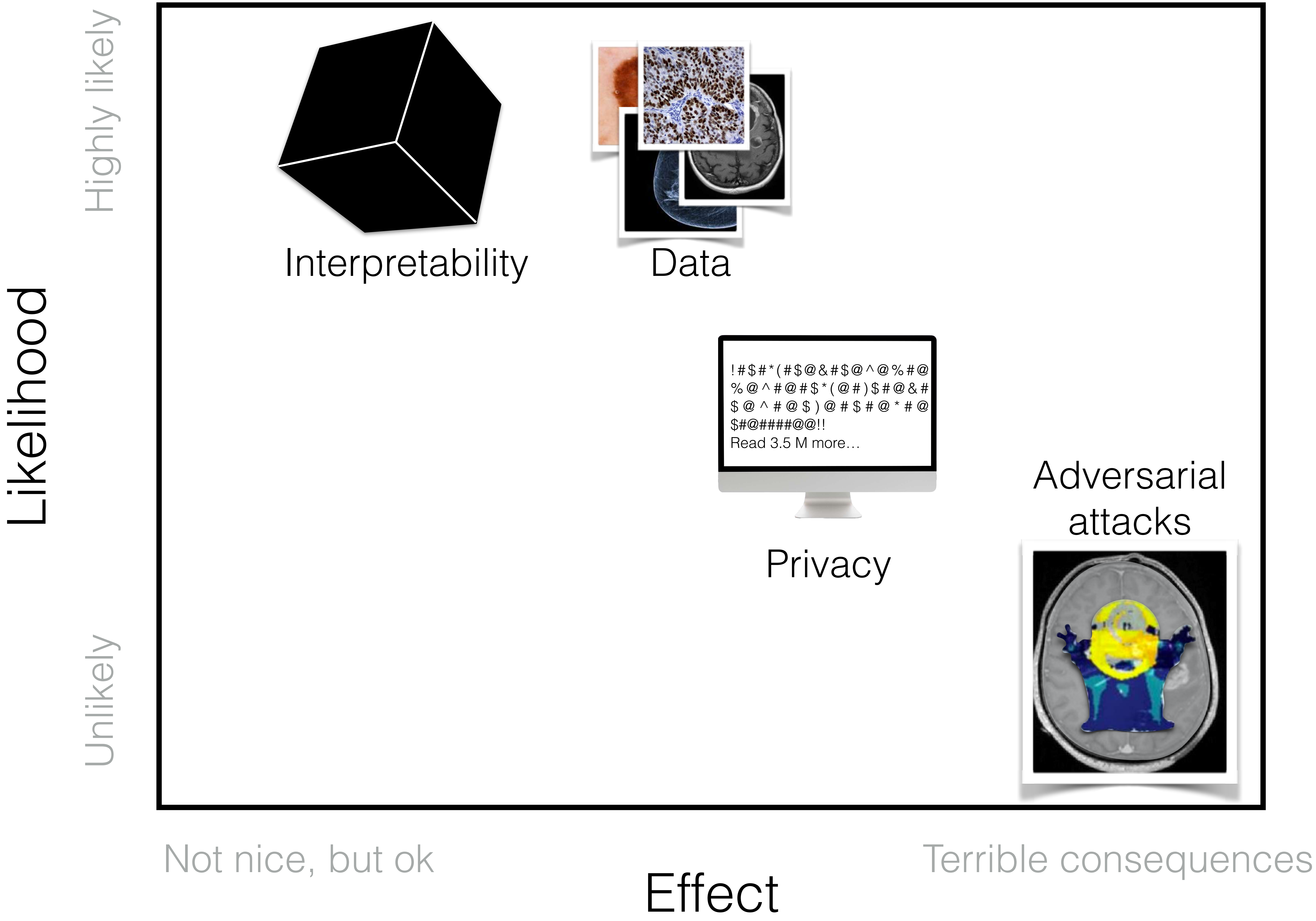


Houdini: Fooling Deep Structured Prediction Models

Moustapha Cisse, Yossi Adi, Natalia Neverova, Joseph Keshet

(Submitted on 17 Jul 2017)

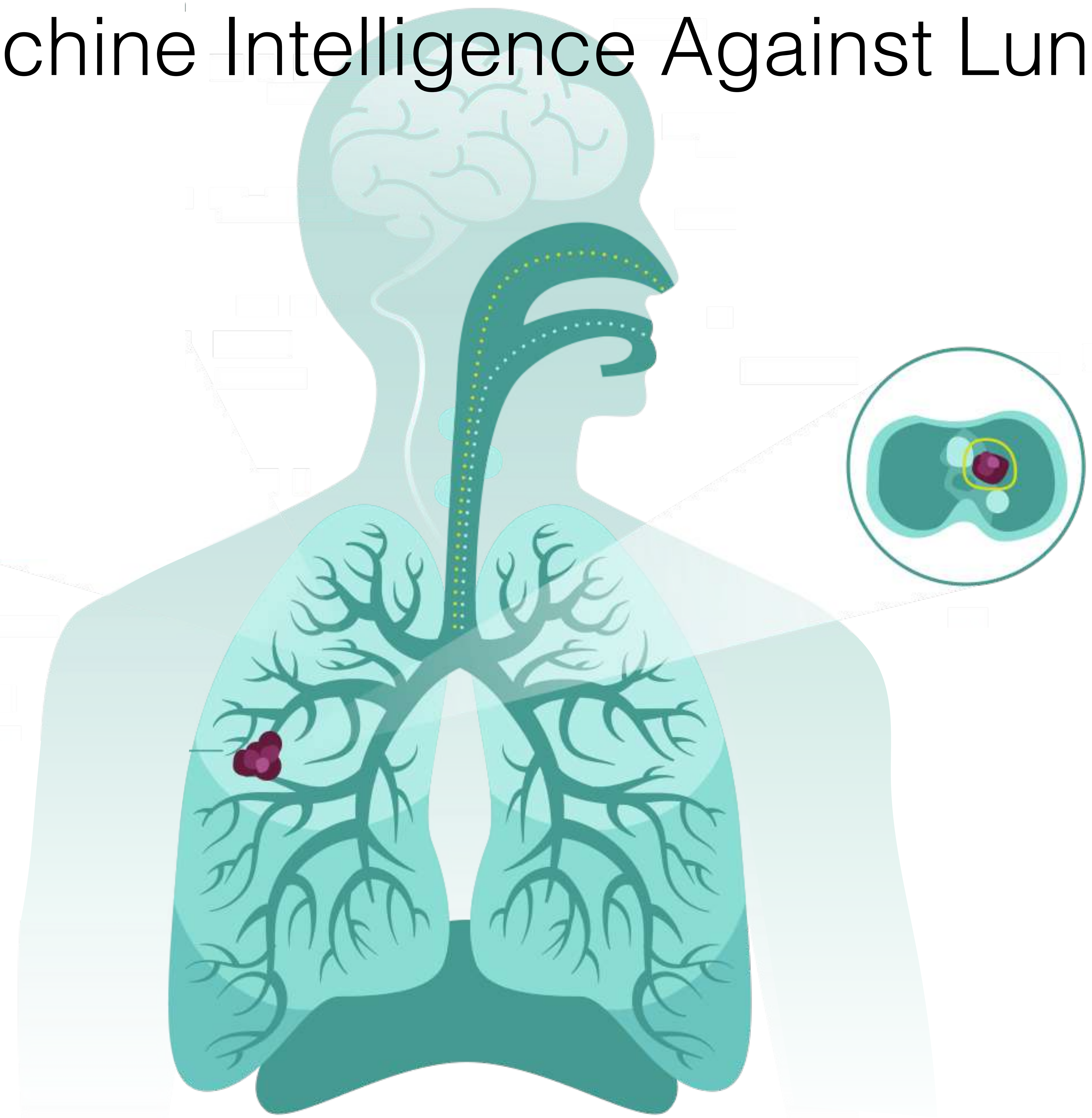
Chart of possible reasons why deep learning may fail to revolutionise medicine



This is all great stuff, what is next?

kaggle.com

Turning Machine Intelligence Against Lung Cancer



NATIONAL DATA SCIENCE BOWL

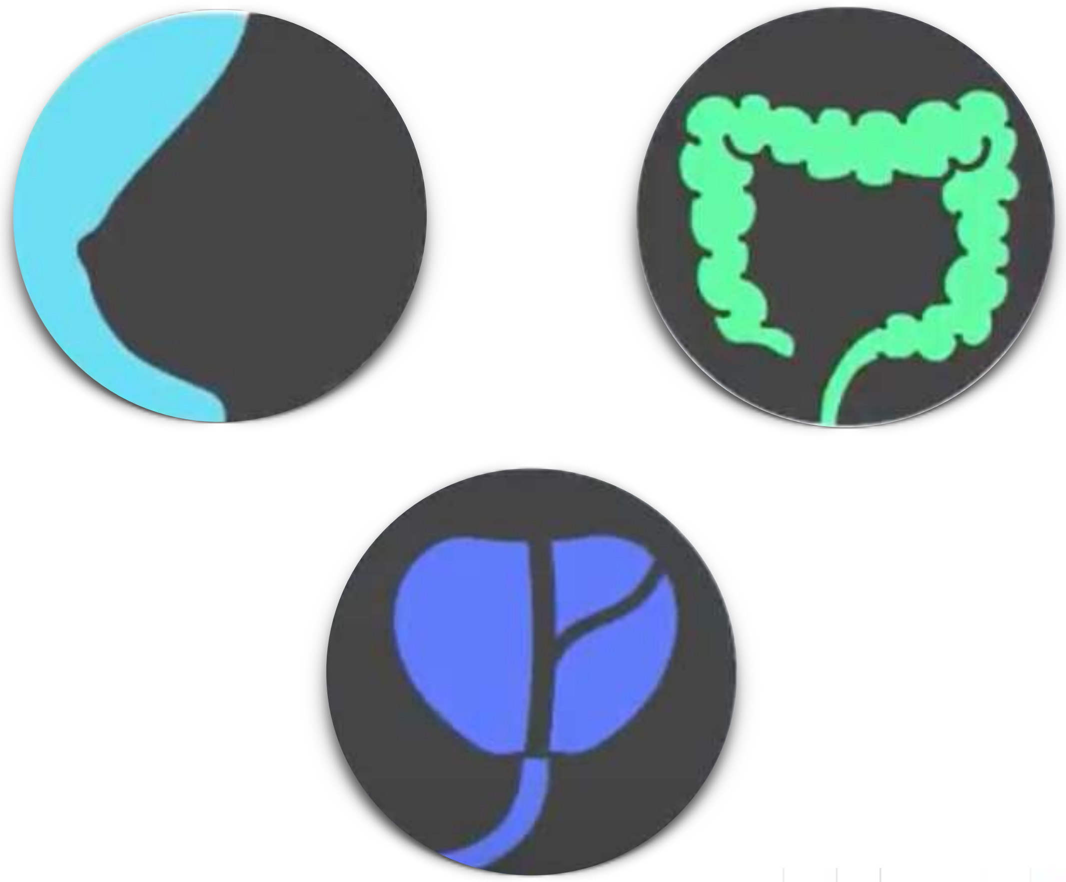
kaggle

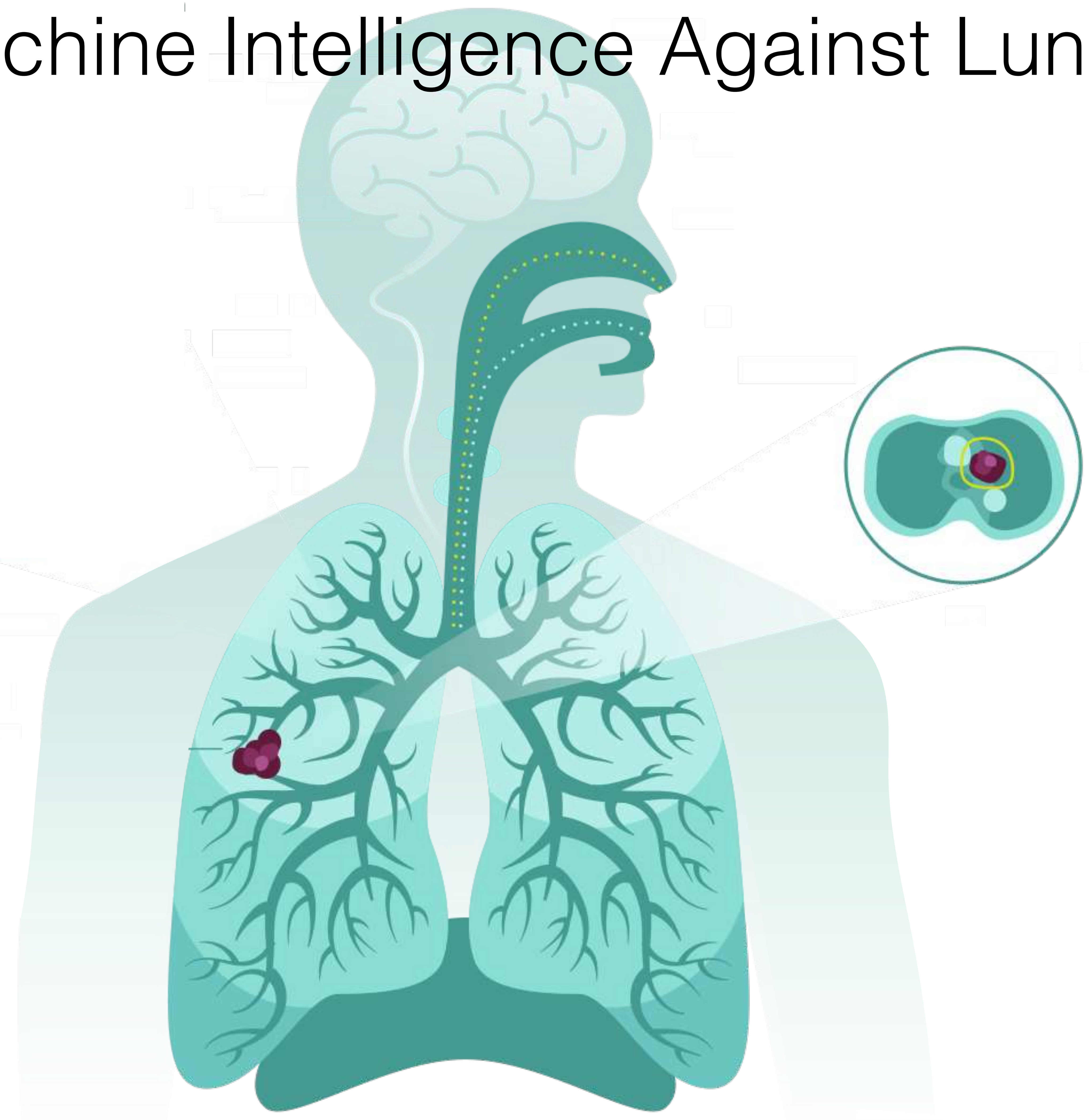
TARTU ÜLIKOOL · UNIVERSITAS TARTUENSIS · 1632

Team: Lauri Listak
Supervisor: Dmytro Fishman

http://www.datasciencebowl.com/competitions/turning-machine-intelligence-against-lung-cancer/

Turning Machine Intelligence Against Lung Cancer





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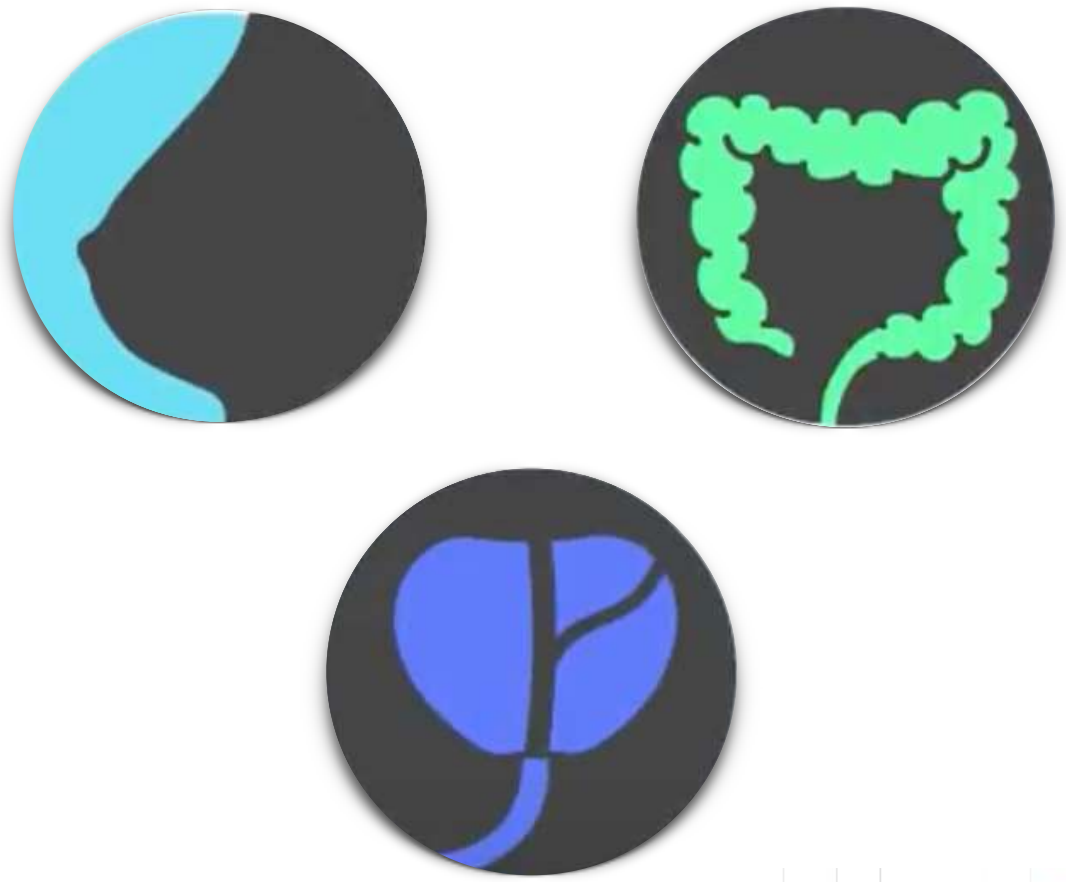
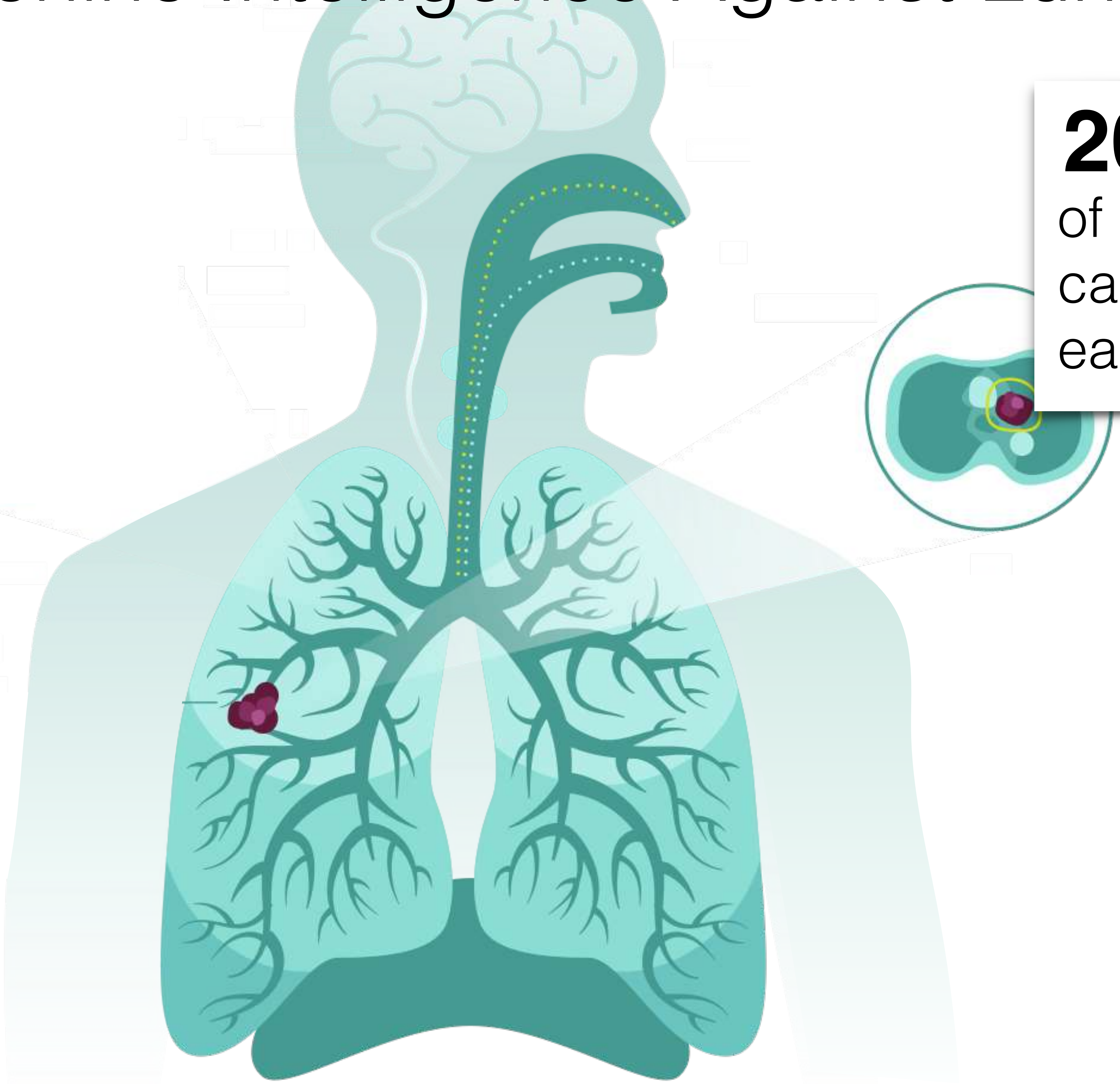
Turning Machine Intelligence Against Lung Cancer





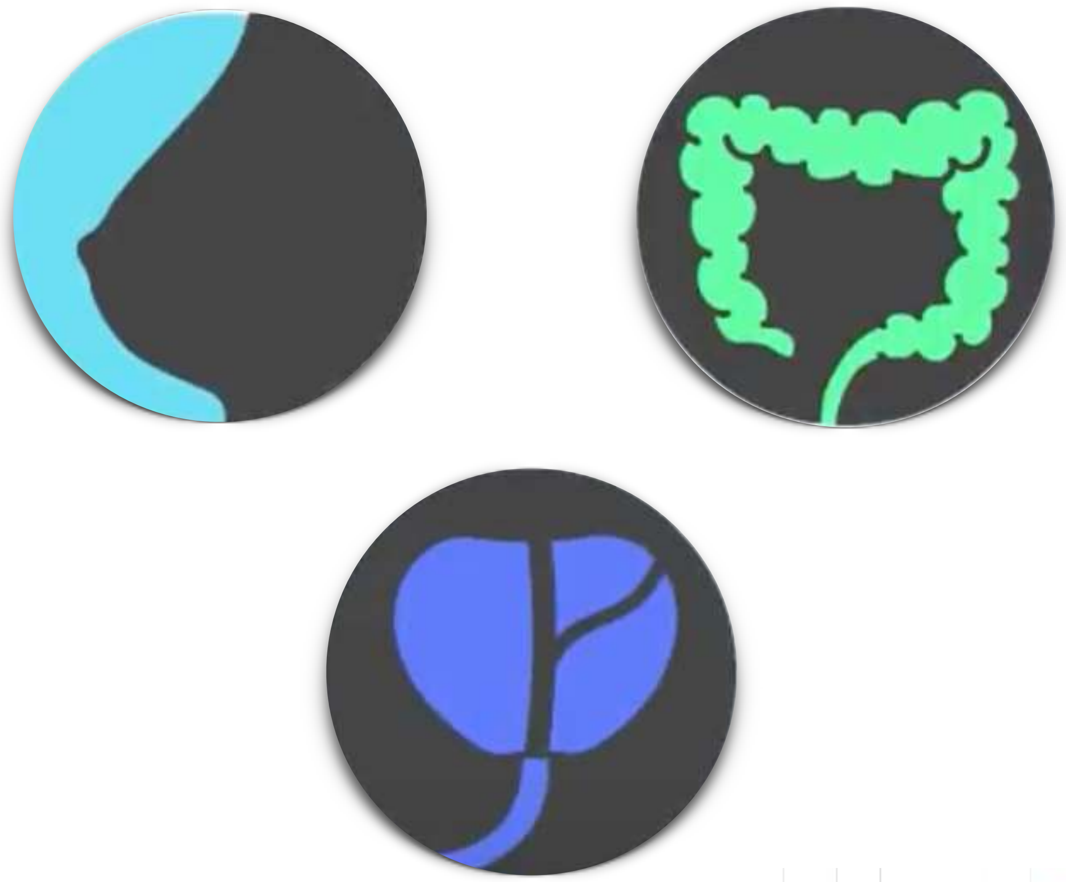
20%

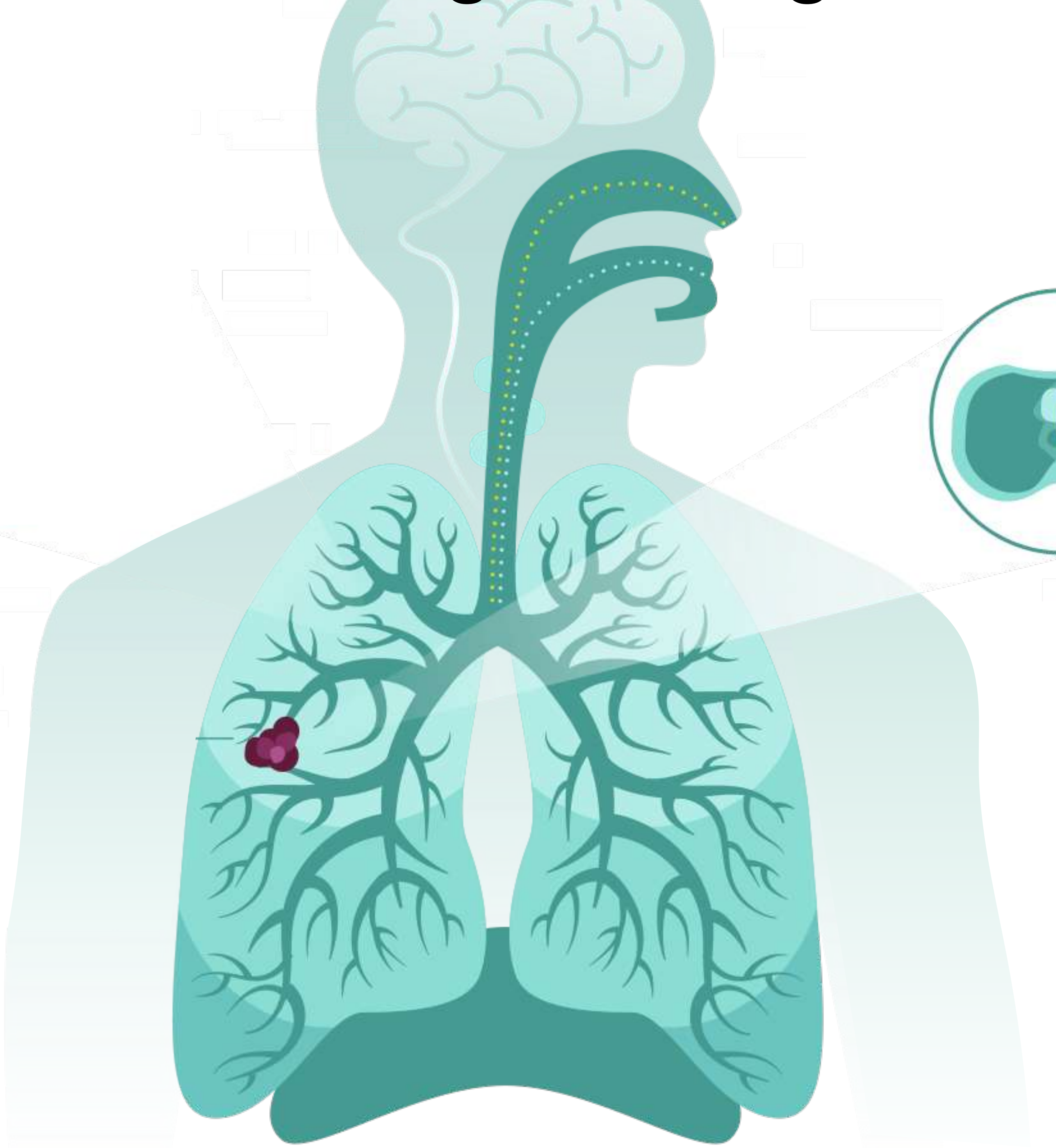
of lung cancer deaths can be **reduced** with early detection

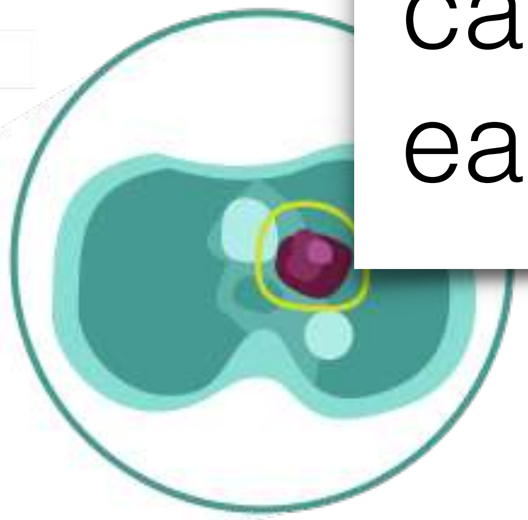
Team: Lauri Listak
Supervisor: Dmytro Fishman

http://www.datasciencebowl.com/competitions/turning-machine-intelligence-against-lung-cancer/

Turning Machine Intelligence Against Lung Cancer







20%
of lung cancer deaths can be **reduced** with early detection

High False Positives rates
lead to interventional treatments, additional **costs** and patient **anxiety**

NATIONAL DATA SCIENCE BOWL

kaggle

TARTU ÜLIKOOL · UNIVERSITAS TARTUENSIS · 1632

Team: Lauri Listak
Supervisor: Dmytro Fishman

http://www.datasciencebowl.com/competitions/turning-machine-intelligence-against-lung-cancer/

BONNIE J. ADDARIO
LUNG CANCER
FOUNDATION

DRIVENDATA

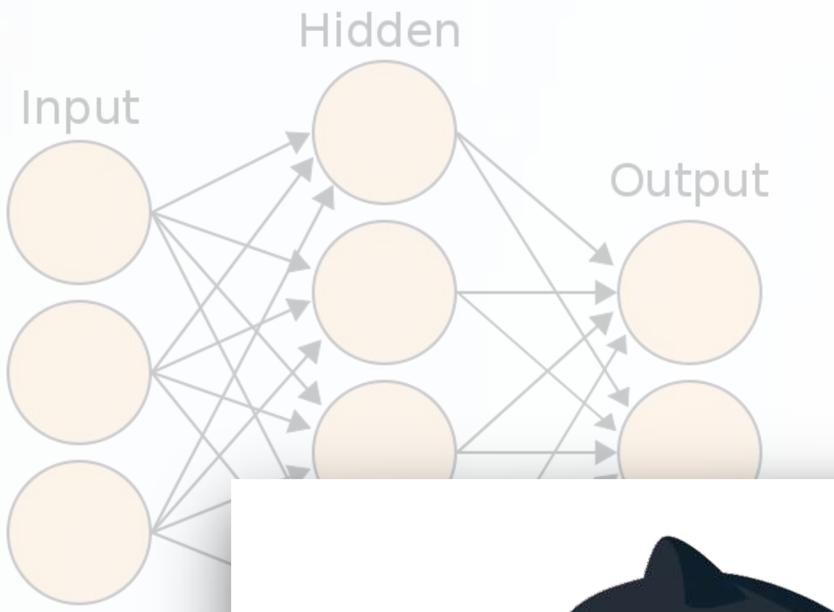
CONCEPT TO CLINIC

2023

CONCEPT TO CLINIC


Hidden
Input
Output
kaggle


Hidden
Input
Output
kaggle



github.com/concept-to-clinic/concept-to-clinic

DREAM
CHALLENGES

powered by Sage Bionetworks

http://dreamchallenges.org/

References

- Series of blog posts "Do machines actually beat doctors?" by **Luke Oakden-Rayner** (https://lukeoakdenrayner.wordpress.com/2016/11/27/do-computers-already-outperform-doctors/)

- Opportunities and obstacles for deep learning in biology and medicine by **Ching et al.** (http://www.biorxiv.org/content/biorxiv/early/2017/05/28/142760.full.pdf)

- Computational biology - deep learning by **William Jones, Kaur Alasoo, Dmytro Fishman et al.** (accepted)


BIIT
When is dinner?
Zzzzzz....
From *complex math* it follows....
Newborn PhD
No grant writing...
Just came from Boston
Can we go now?
Zzzzzz....
What a hell am I doing here?

dmytro@ut.ee


Rocket science is for kids…
Bioinformatics & Medicine are for scientists