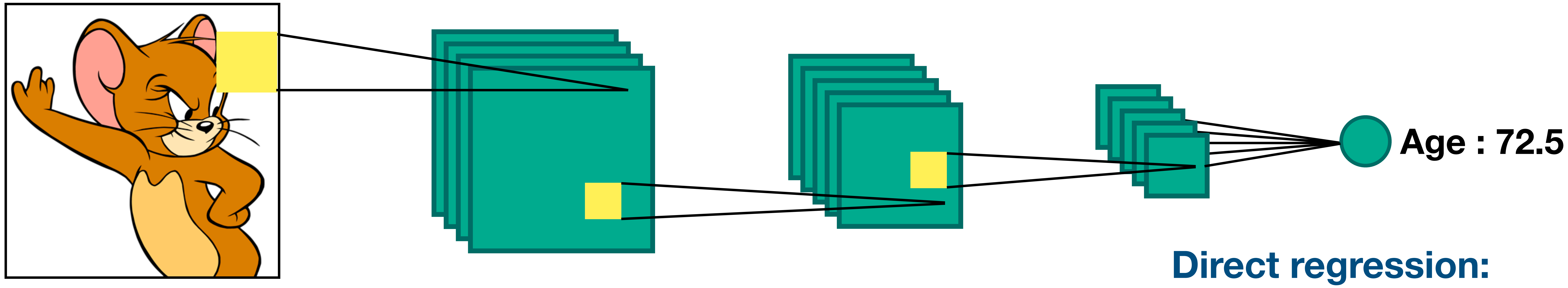
Label Encoding for Regression Networks

https://medium.com/typeiqs/advanced-lane-finding-c3c8305f074

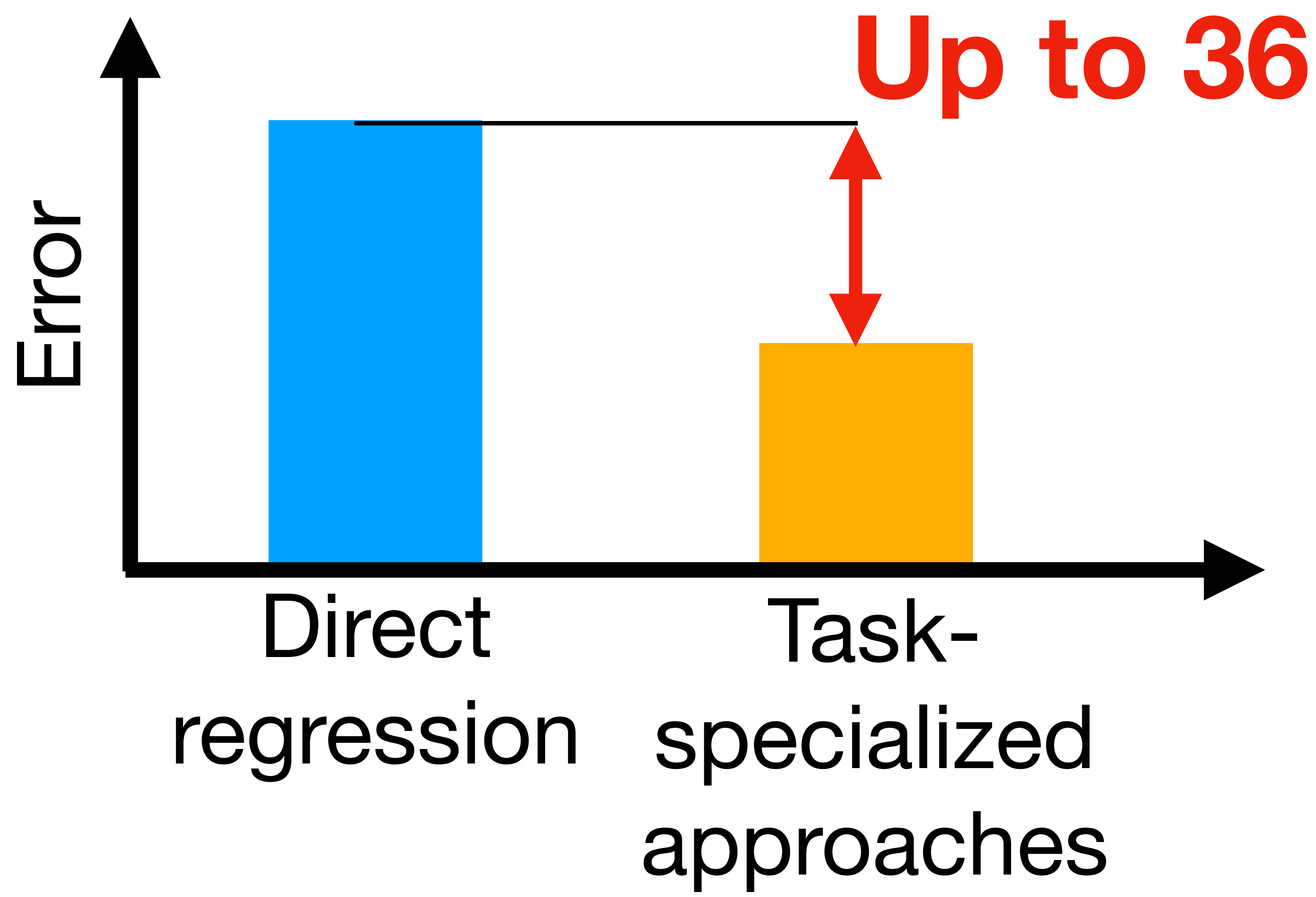


https://www.pngwing.com/en/free-png-ypjtl

Direct regression:

(Predicted value - Target value)^2

https://www.roboticsbusinessreview.com/opinion/
slam-machine-learning-ushers-in-the-age-of-perception/



Deval Shah, Zi Yu Xue, Tor M. Aamodt

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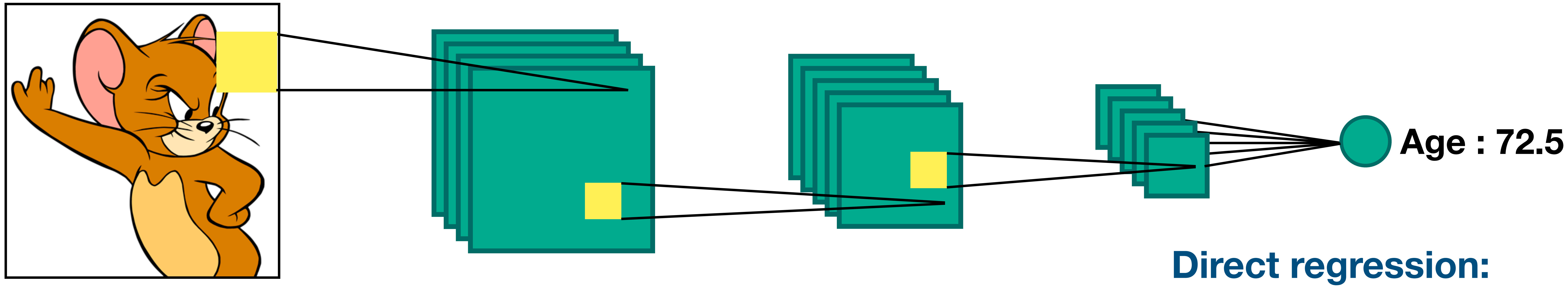

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Direct regression:

(Predicted value - Target value)^2

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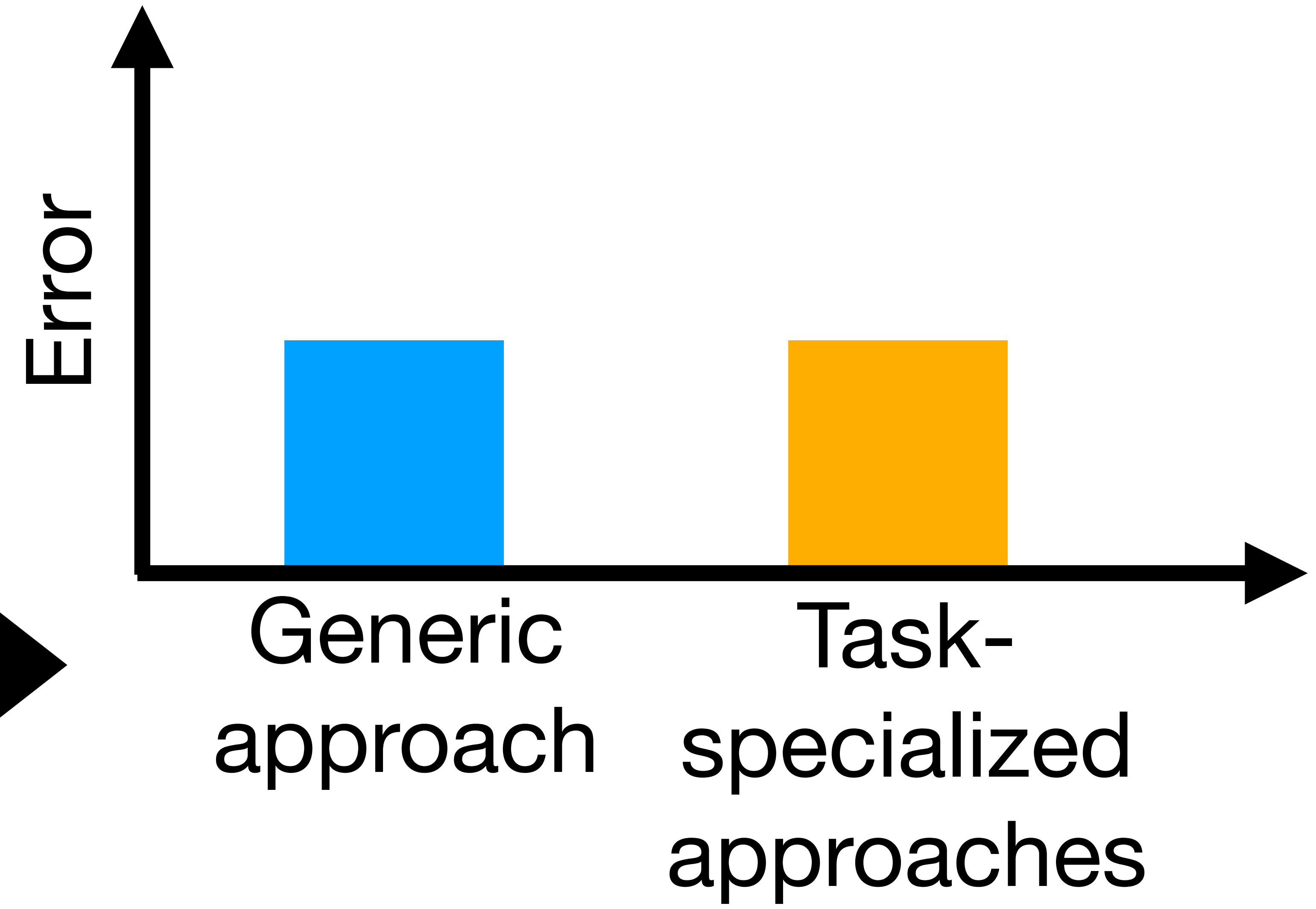
We propose a
generic regression approach
“Binary Encoded Labels”



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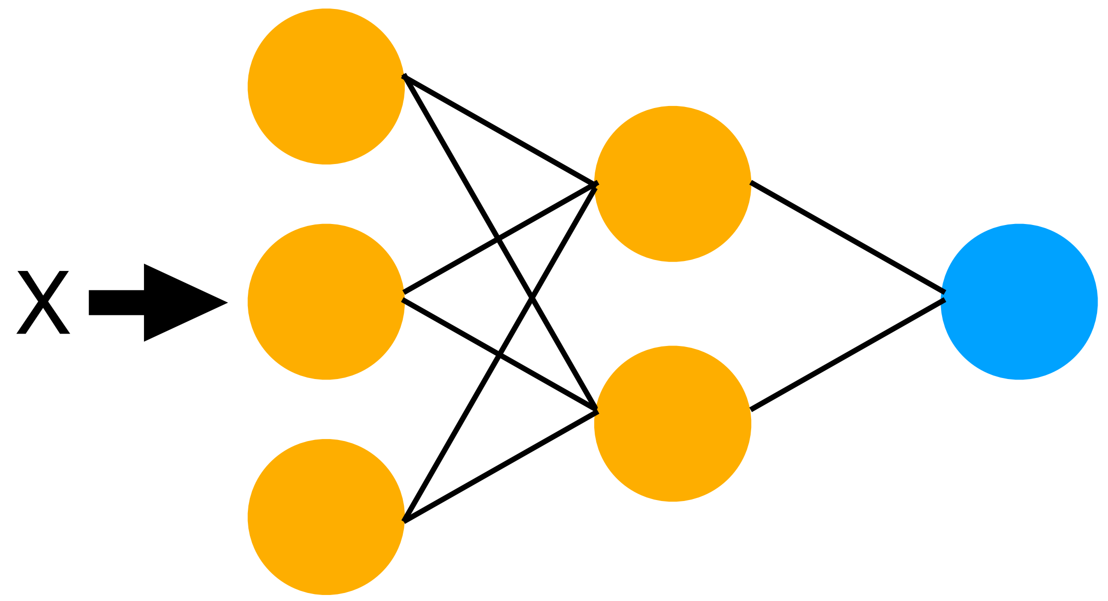
Binary Encoded Labels (BEL)

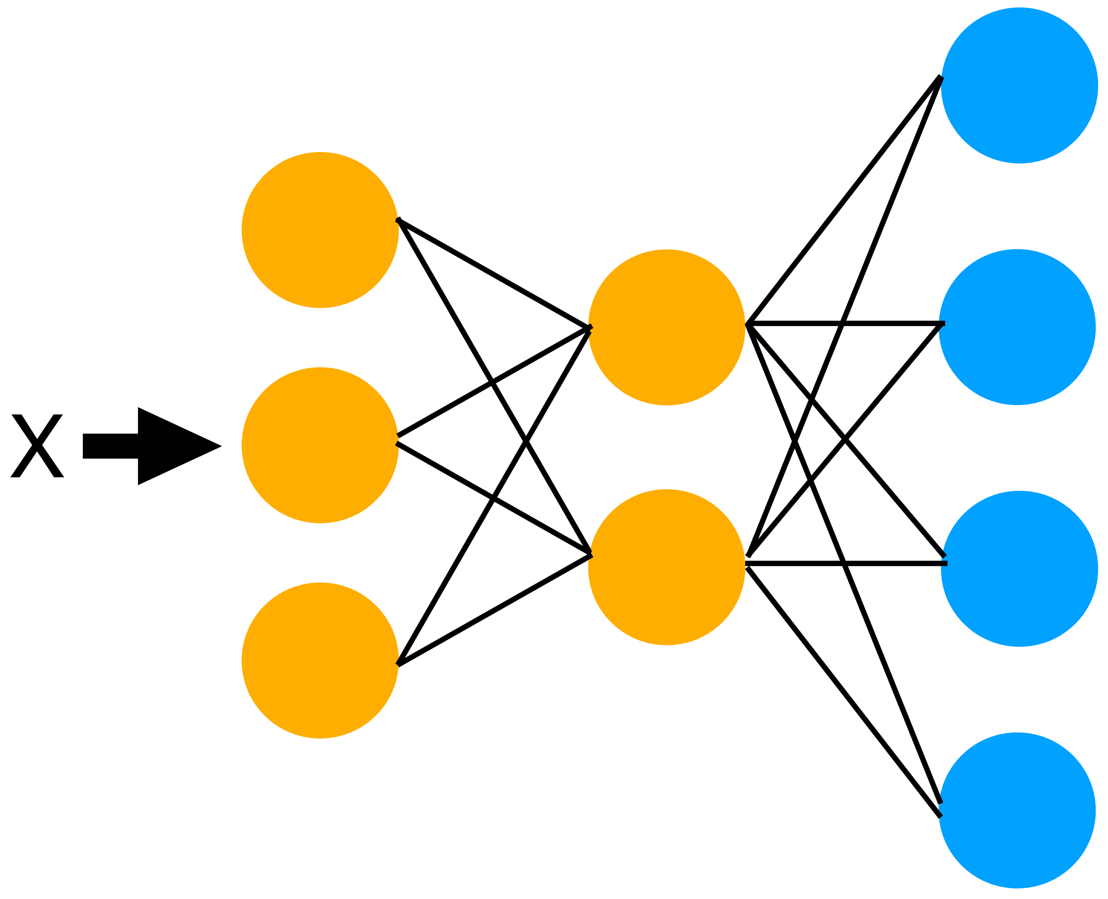
Regression



$Y \in \mathbb{R}$

Binary Encoded Labels (BEL)

Regression by Binary Classification



$Y_0 \in \{0,1\}$

$Y_1 \in \{0,1\}$

$Y_2 \in \{0,1\}$

$Y_3 \in \{0,1\}$

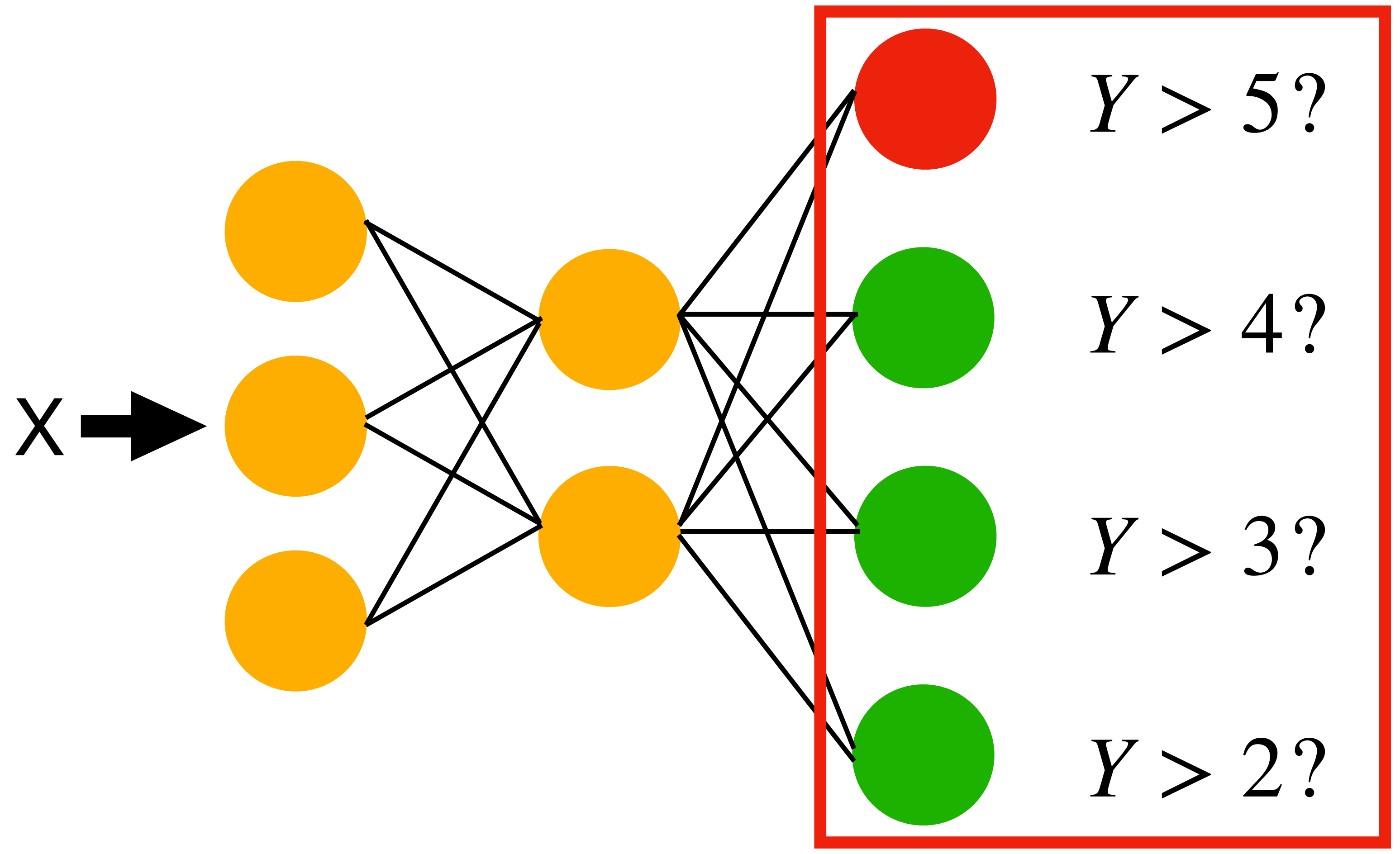
Real-valued prediction

http://www.clipartpanda.com/clipart_images/struggling-uphill-man-with-58696904

Since binary classification is a well-studied problem, **regression by binary classification** can significantly reduce design, implementation, and analysis efforts.

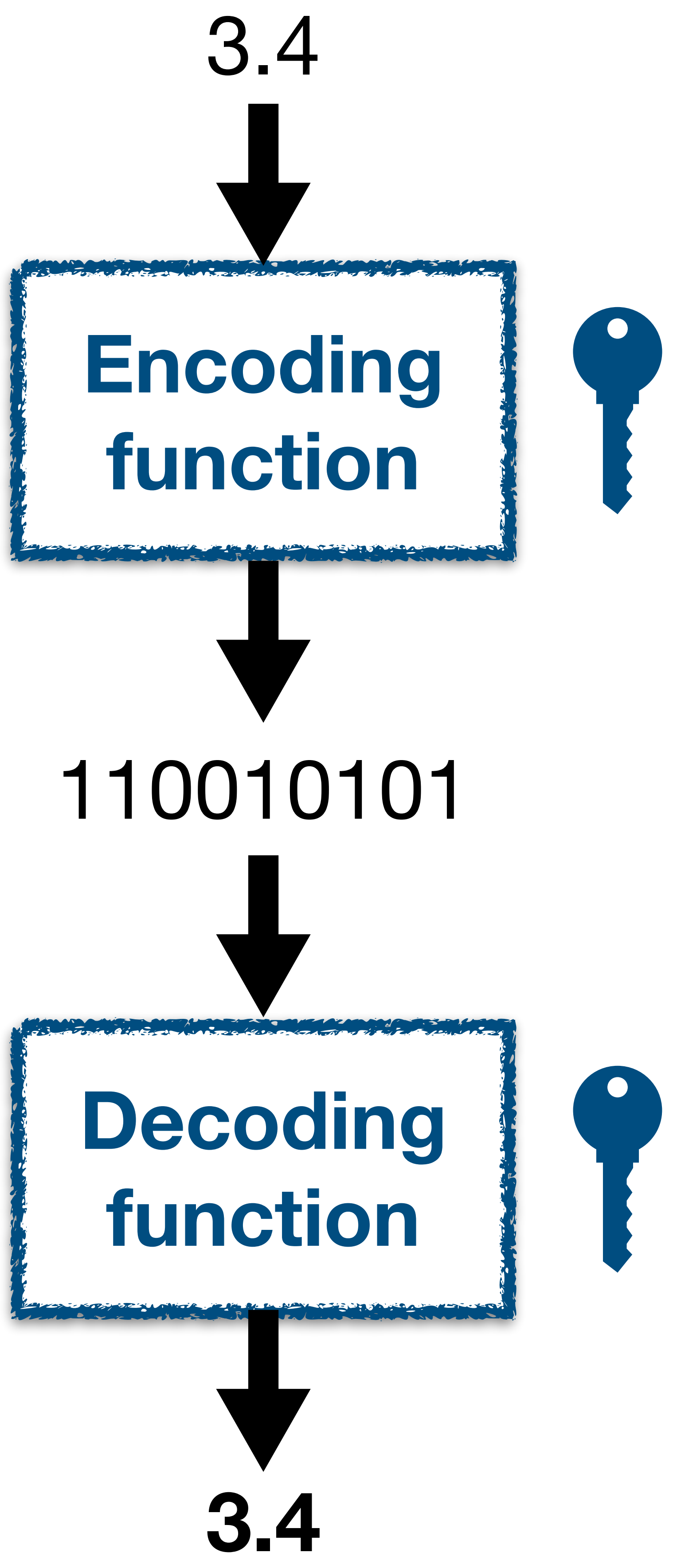
Binary Encoded Labels (BEL)

Setup used by current approaches



$Y \in (2,3]$	$Y \in (3,4]$	$Y \in (4,5]$
0	0	0
0	0	1
0	1	1
1	1	1

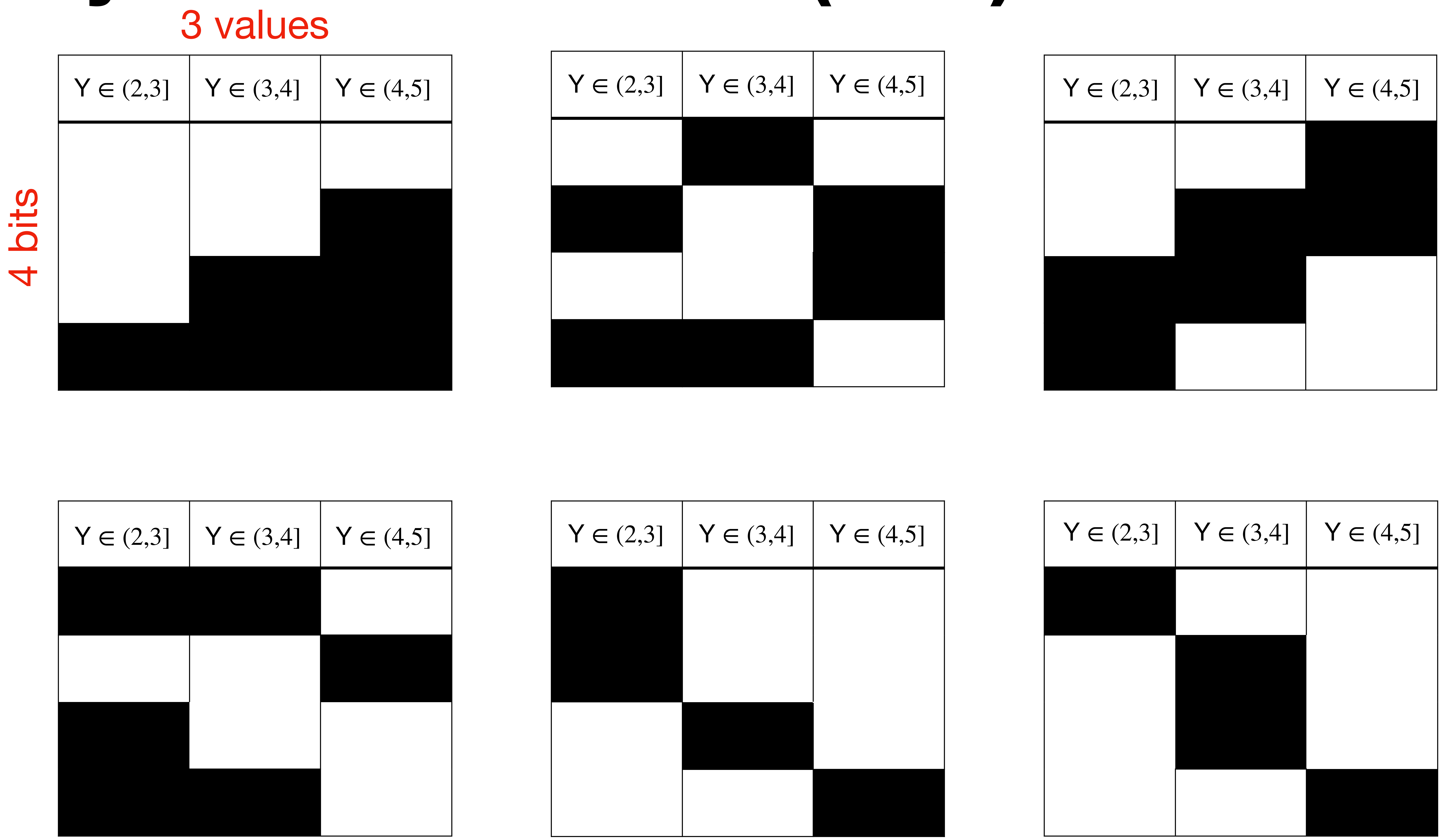
Generalization of regression by binary classification (BEL)



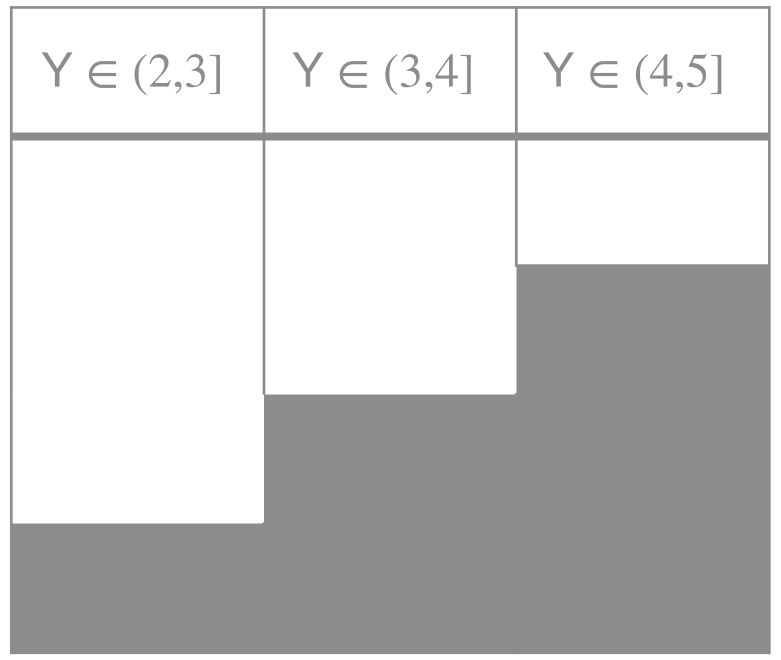
[1] Ling Li and Hsuan-Tien Lin. Ordinal regression by extended binary classification, NIPS 2006

[2] Huan Fu, Mingming Gong, Chaohui Wang, Kayhan Batmanghelich, and Dacheng Tao. Deep Ordinal Regression Network for Monocular Depth Estimation, CVPR 2018

Binary Encoded Labels (BEL)

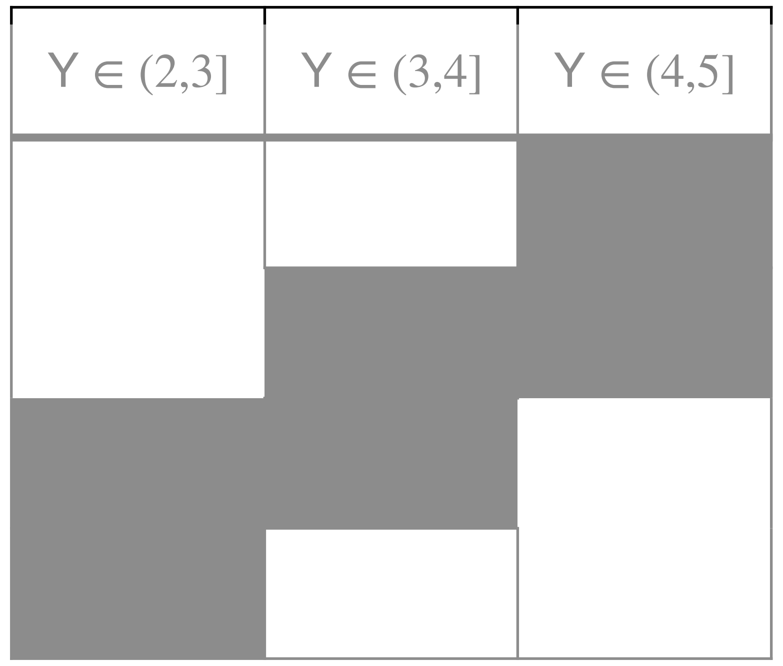


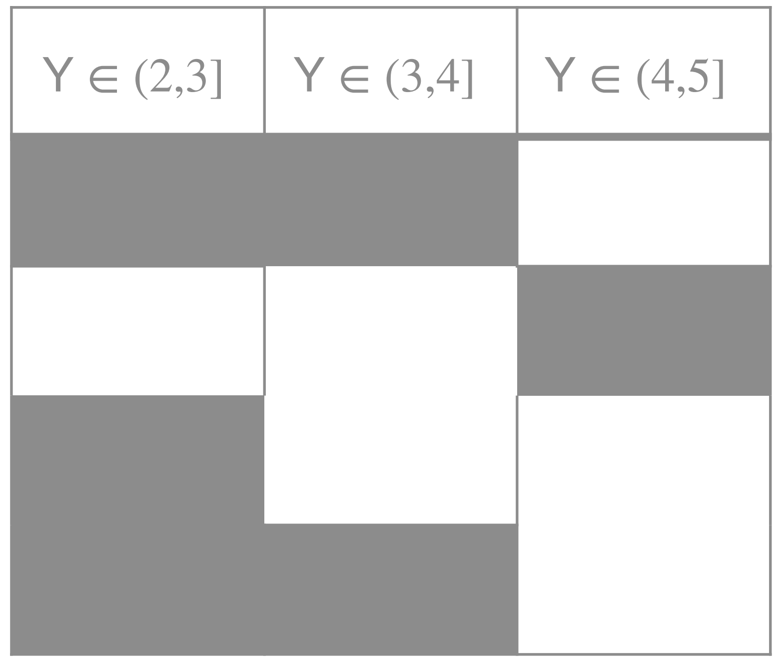
Binary Encoded Labels (BEL)

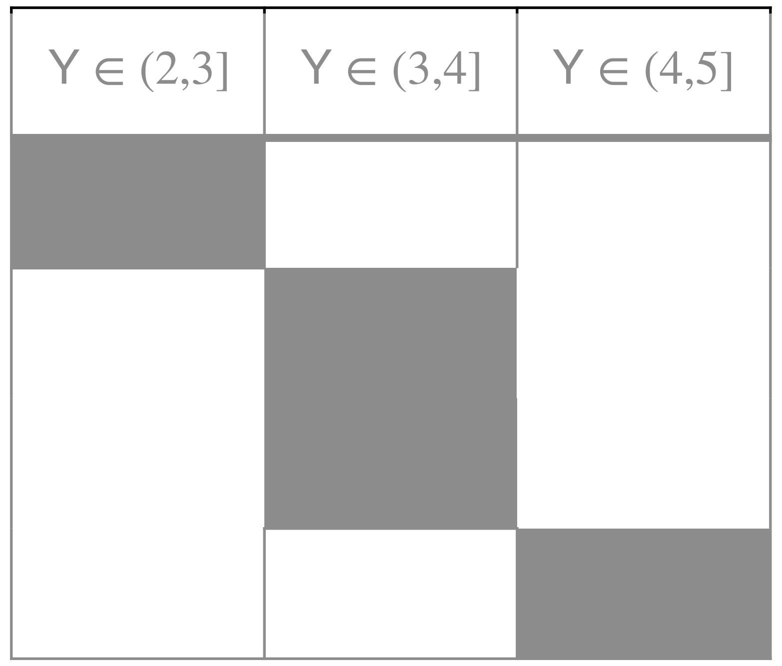


Number of possible encodings for
M bits
N values

$$\frac{2^M!}{(2^M - N)!} \Rightarrow \frac{2^8!}{(2^8 - 64)!} \Rightarrow 10^{89}$$







https://www.300feetout.com/stories/3-ways-psychology-and-design-are-linked/homer-simpson-options/

Binary Encoded Labels (BEL)

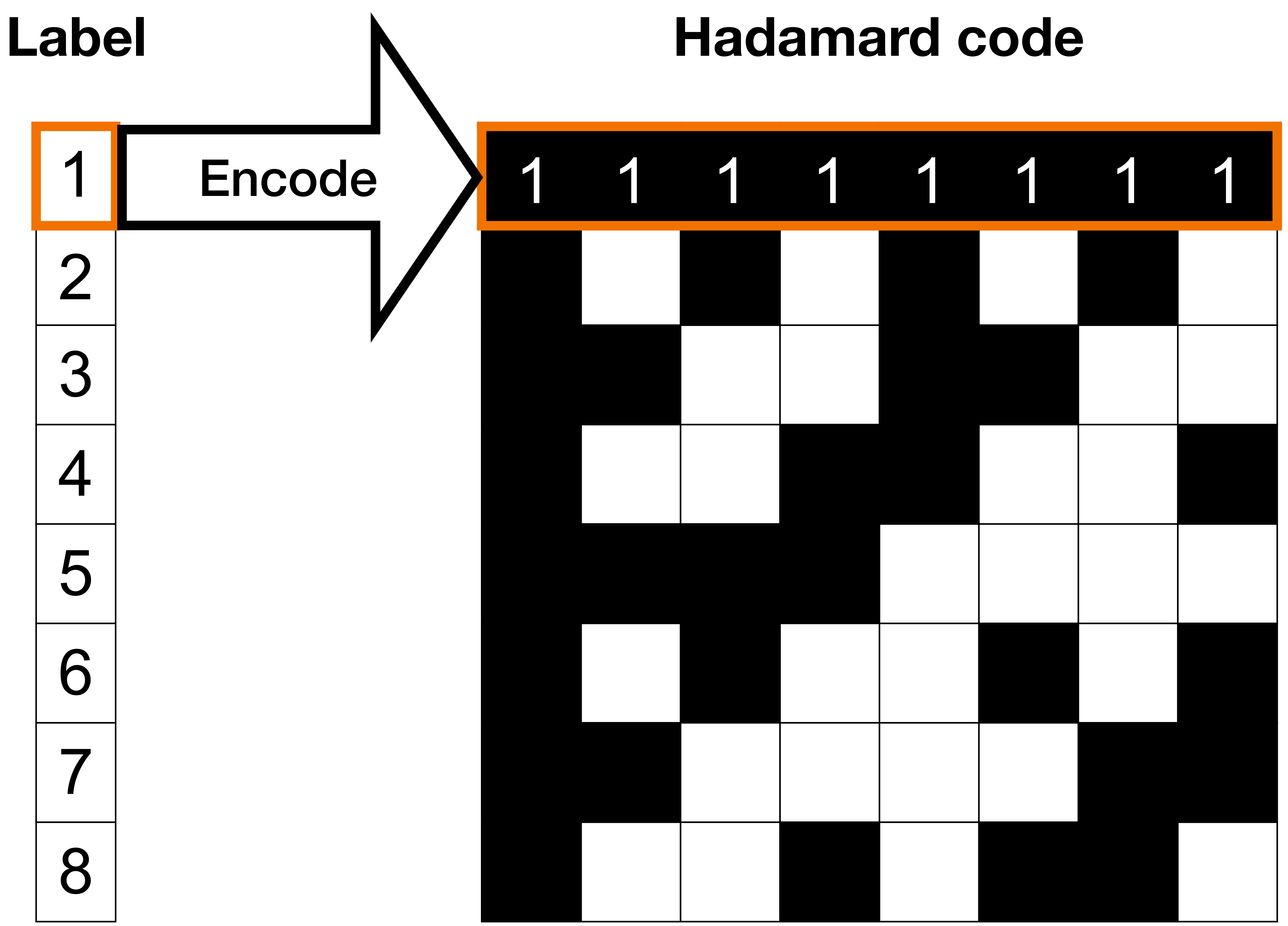
- Encoding design is crucial as different codes result in up to **500% higher errors** than empirically found best code.
- However, there has not been a systematic study on this.

https://www.pngegg.com/en/png-iknaj

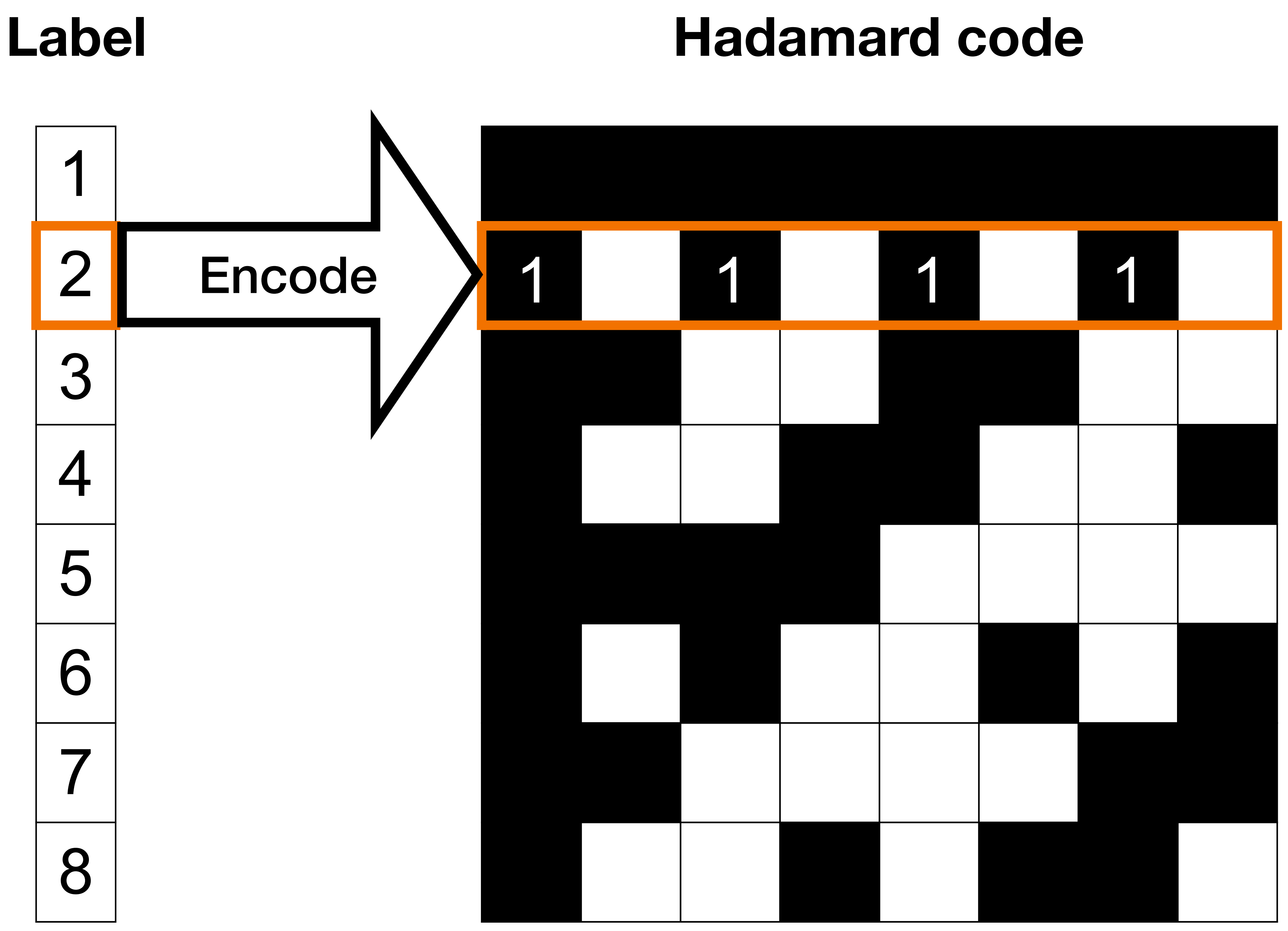
Encoding Design

Label	Error-correction Hadamard code							
1	1	1	1	1	1	1	1	1
2	1	0	1	0	1	0	1	0
3	1	1	0	0	1	1	0	0
4	1	0	0	1	1	0	0	1
5	1	1	1	1	0	0	0	0
6	1	0	1	0	0	1	0	1
7	1	1	0	0	0	0	1	1
8	1	0	0	1	0	1	1	0

Encoding Design

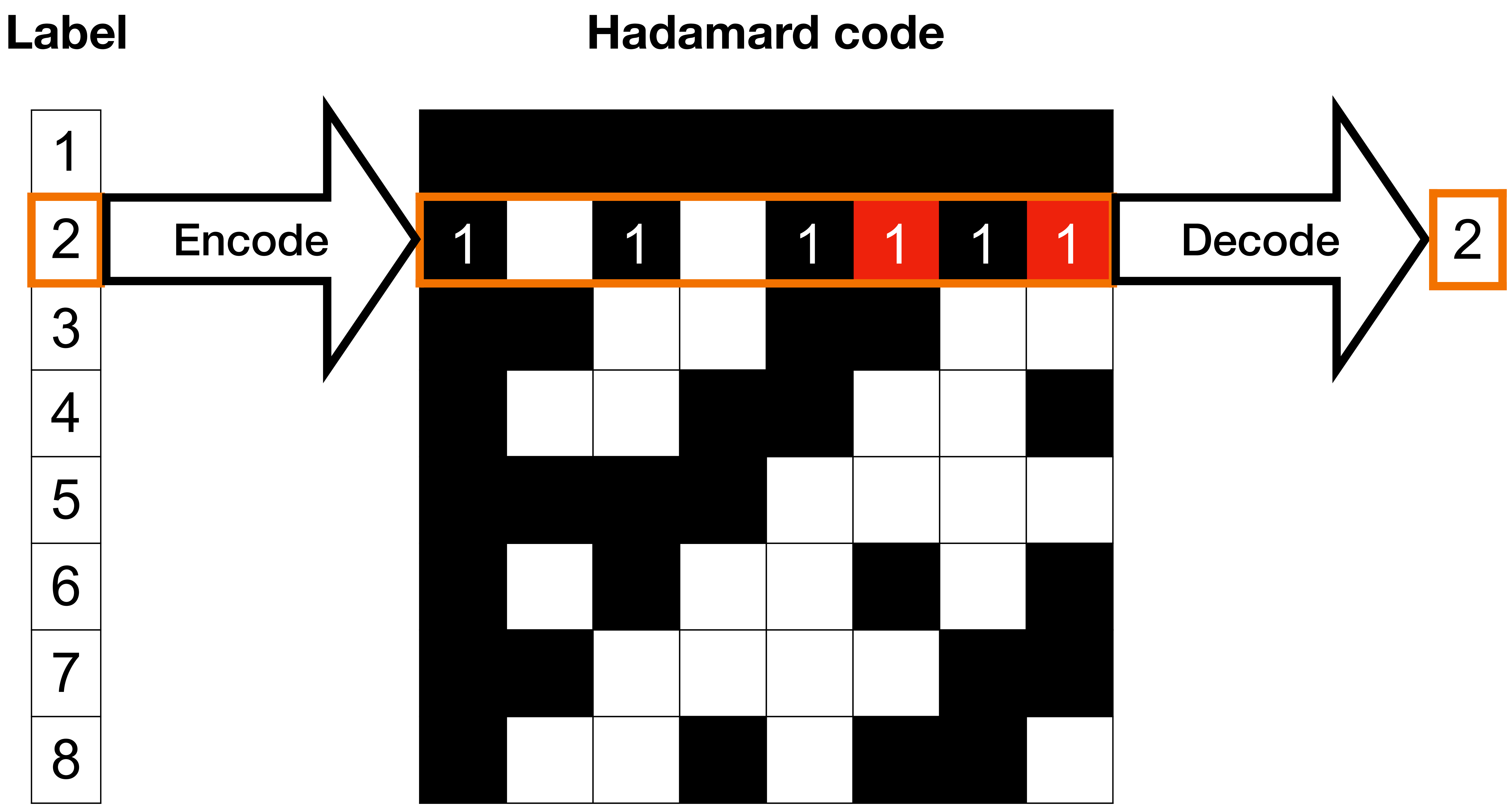


Encoding Design



Encoding Design

- Hadamard code has excellent error-correction properties.
- It is used by existing works on multiclass classification.

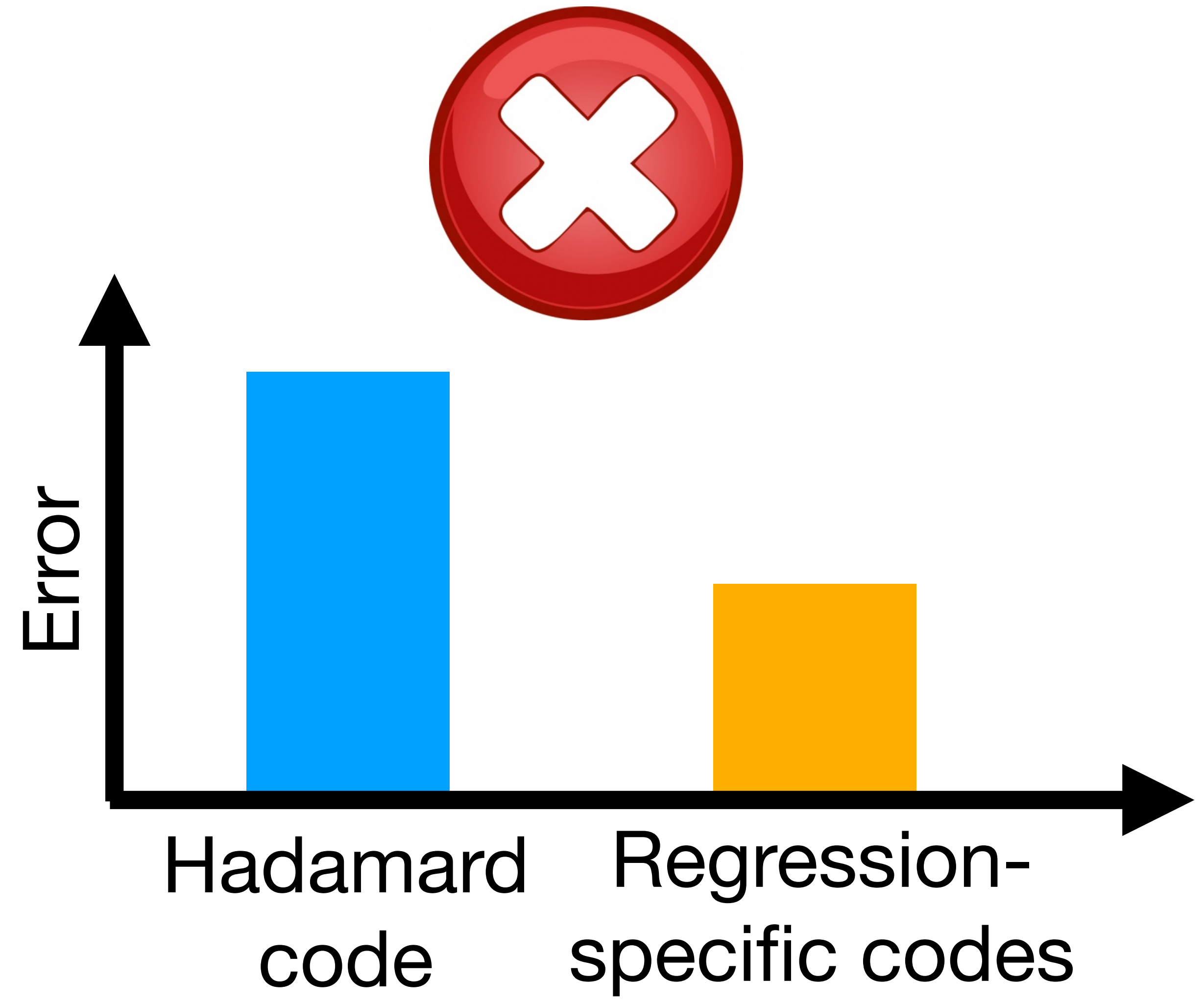


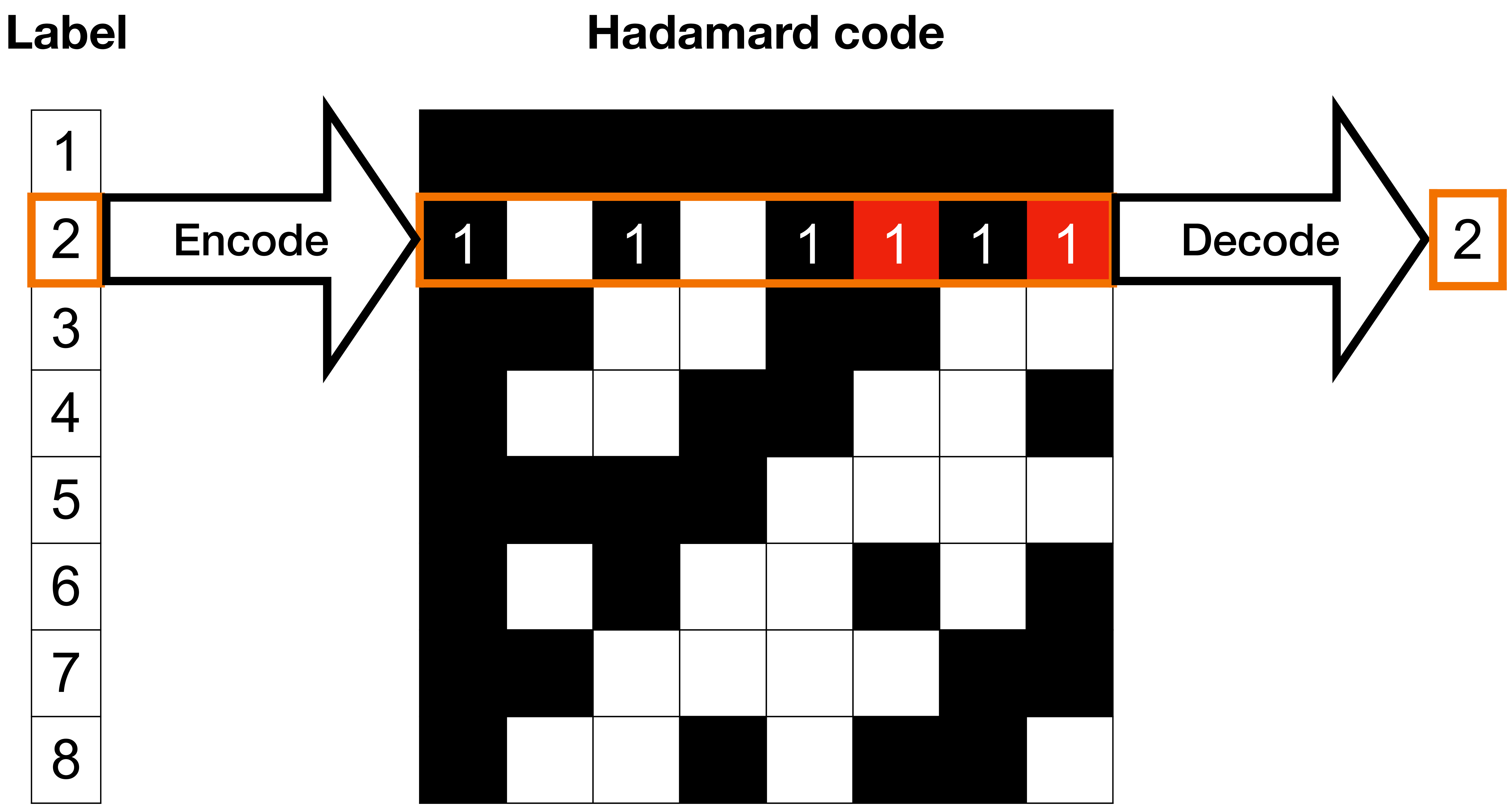
[1] T. G. Dietterich and G. Bakiri. Solving Multiclass Learning Problems via Error-Correcting Output Codes. *Journal of Artificial Intelligence Research*, 1995.

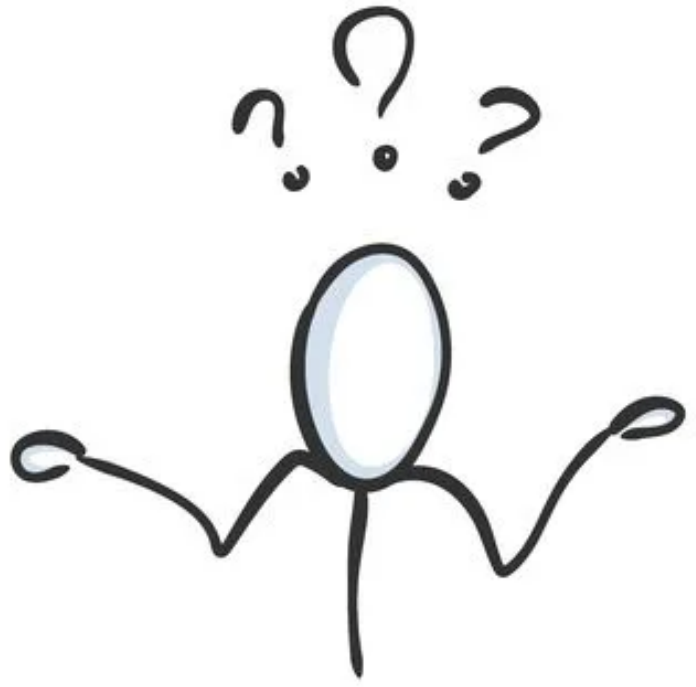
[2] Gunjan Verma and Ananthram Swami. Error correcting output codes improve probability estimation and adversarial robustness of deep neural networks, NeurIPS, 2019.

Encoding Design

We find that the Hadamard code is not suitable for regression!







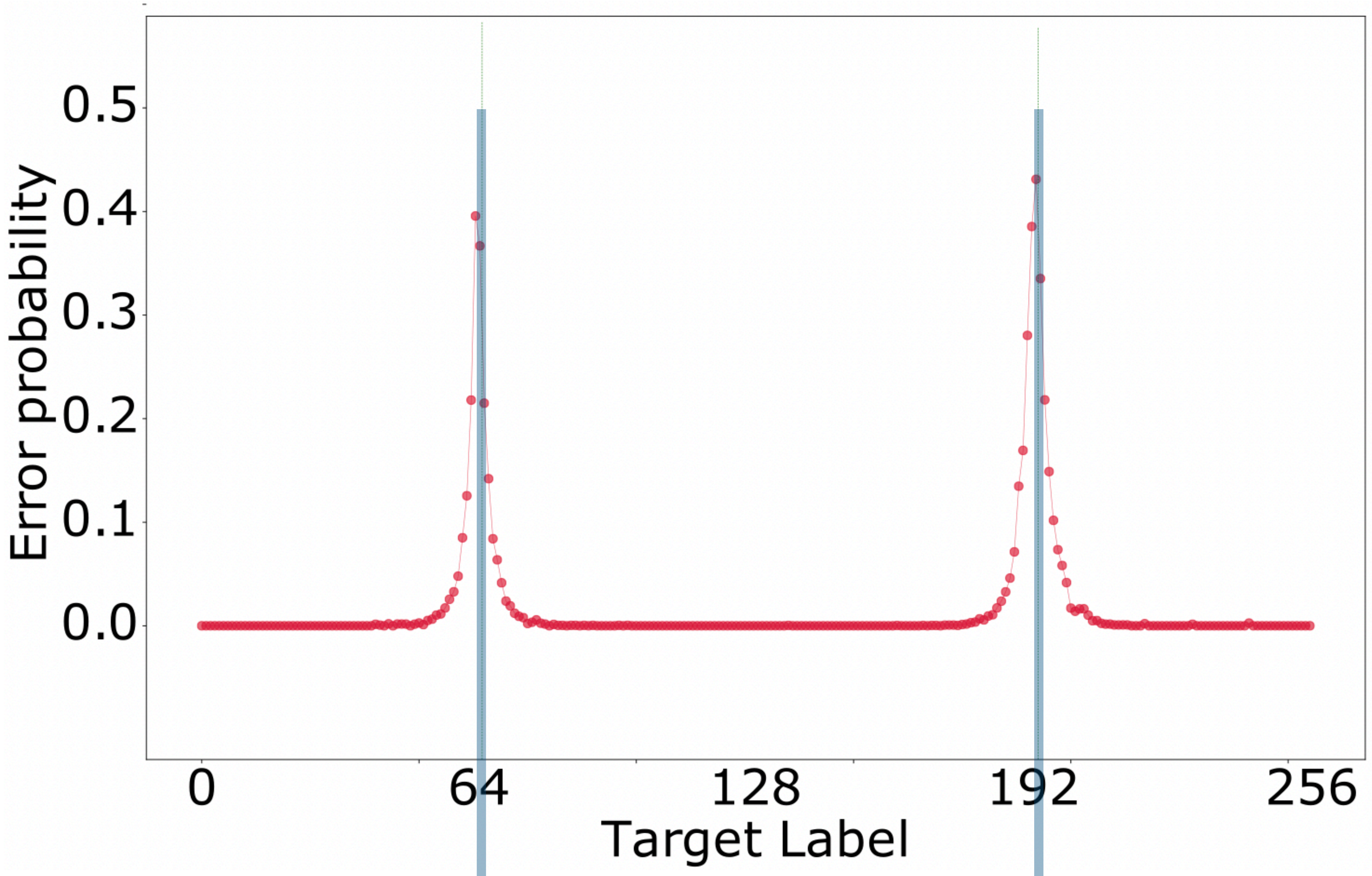
[1] T. G. Dietterich and G. Bakiri. Solving Multiclass Learning Problems via Error-Correcting Output Codes. *Journal of Artificial Intelligence Research*, 1995.

[2] Gunjan Verma and Ananthram Swami. Error correcting output codes improve probability estimation and adversarial robustness of deep neural networks, NeurIPS, 2019.

Encoding Design - Key Insight (1)

Target label	0	…	63	64	65	…	…	190	191	192	…	255
Classifier's target	0	0	0	1	1	1	1	1	1	0	0	0

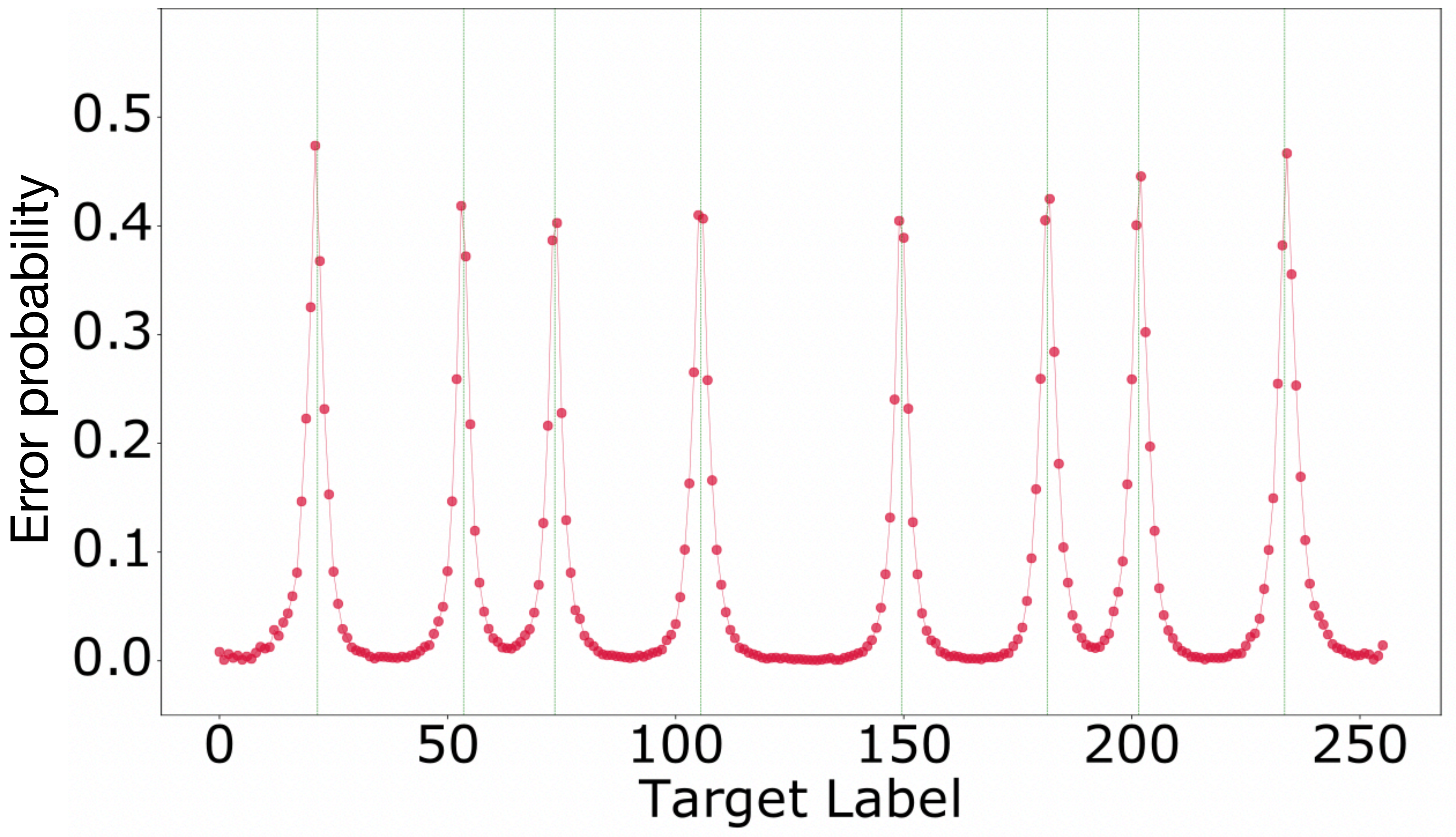
Encoding Design - Key Insight (1)



Target label	0	…	63	64	65	…	…	190	191	192	…	255
Classifier's target	0	0	0	1	1	1	1	1	1	0	0	0

The classifier has a non-uniform error probability for different label values, and it depends on the bit transitions' placement in the code.

Encoding Design - Key Insight (1)



Classifier's target	0..0	11..1	0.0	11..1	00….00	11..1	0.0	11..1	0..0

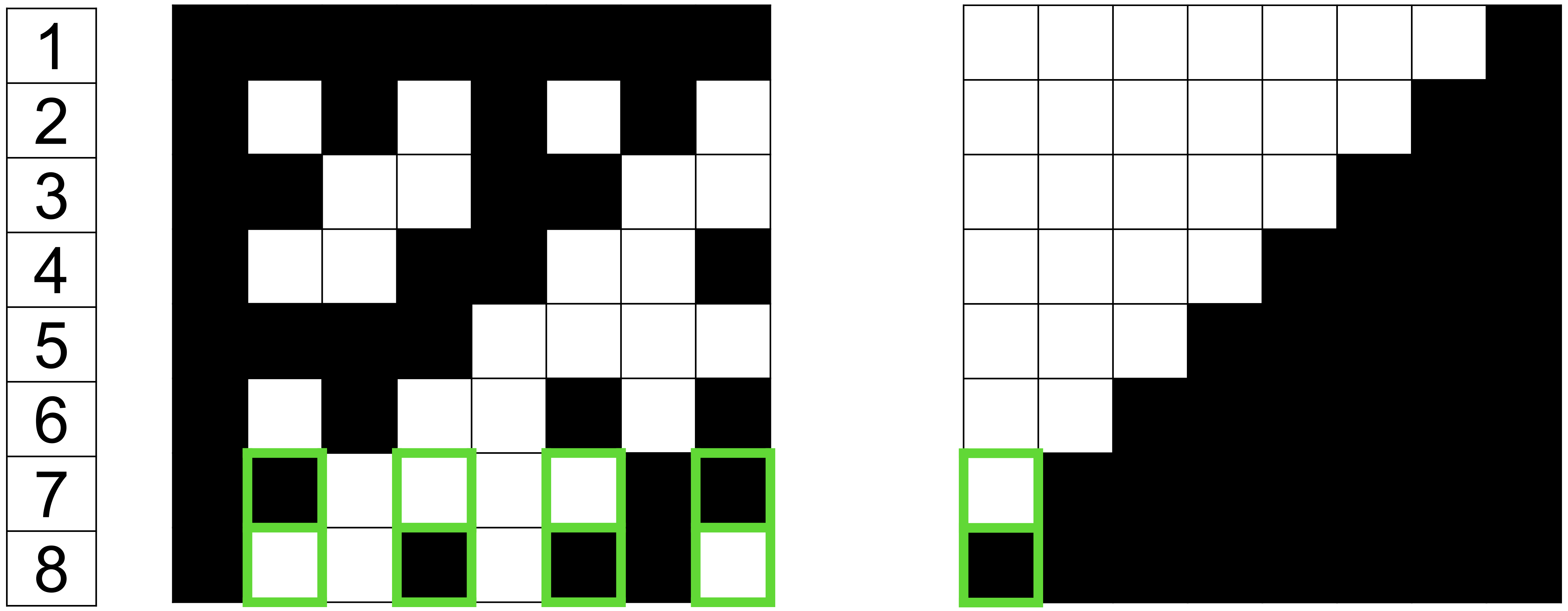
A classifier's decision boundary becomes more complex with more bit transitions, which degrades its accuracy.

Encoding Design - Key Insight (1)

Bit-error probability

Error-correction capability

Label **Hadamard code** **Unary code**

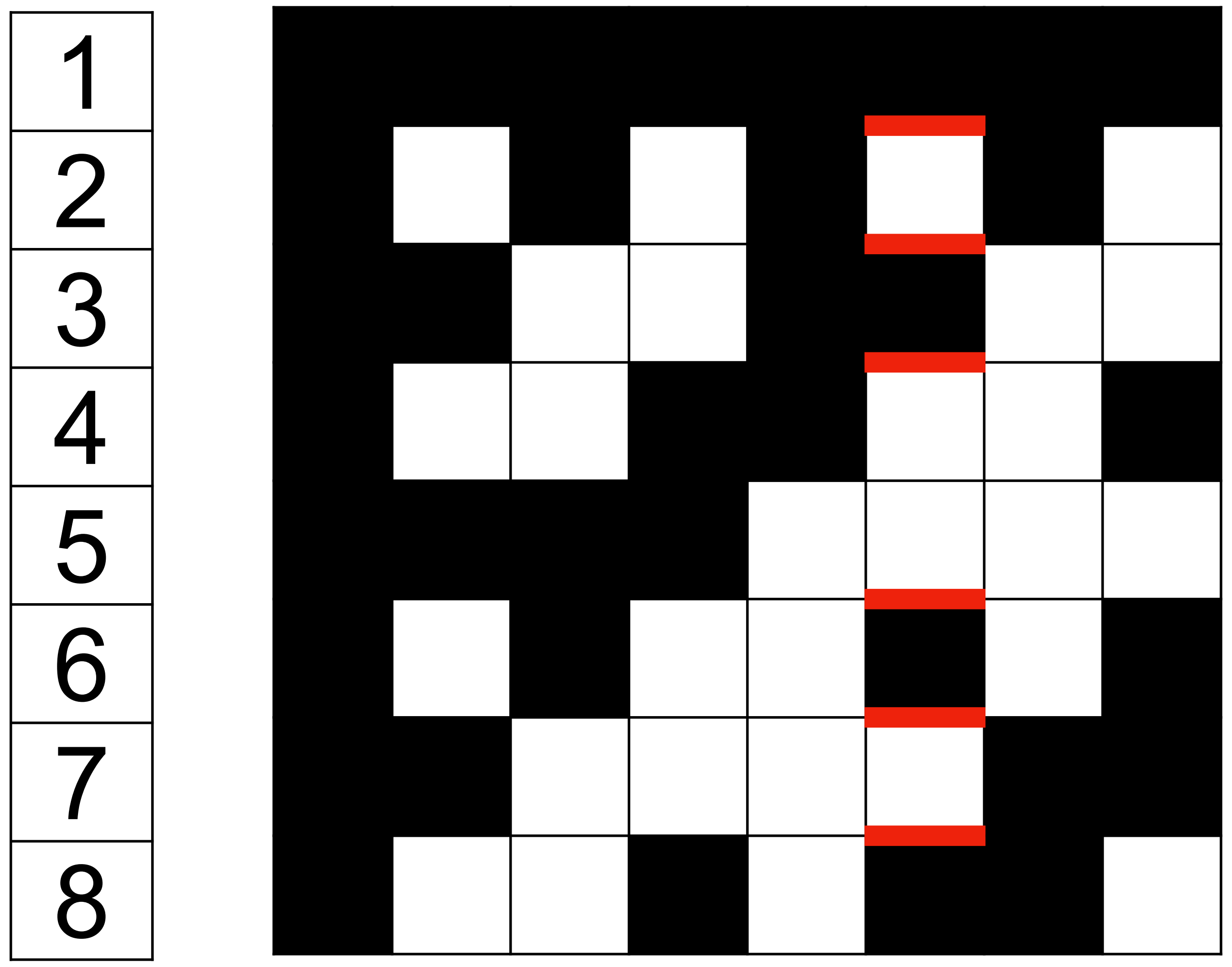
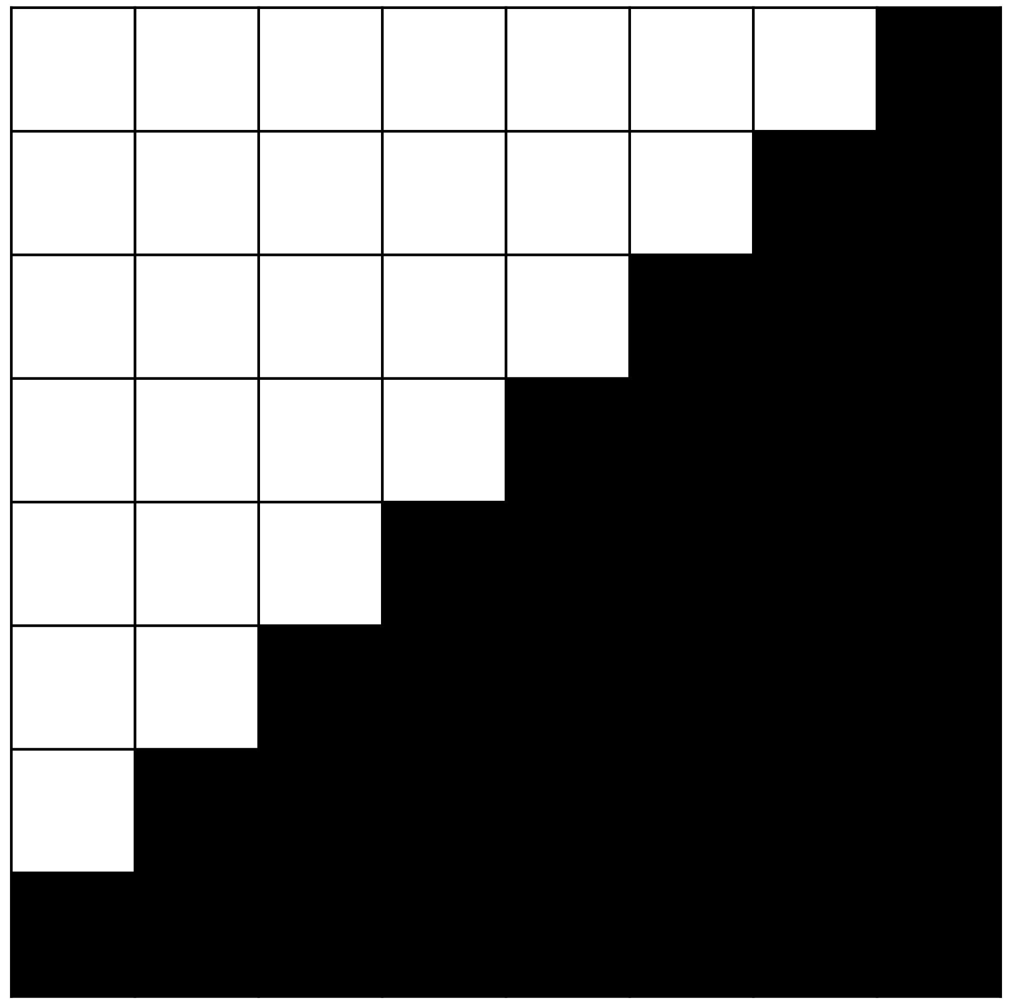


Hamming Distance	**4**	**1**

Encoding Design - Key Insight (1)

Bit-error probability

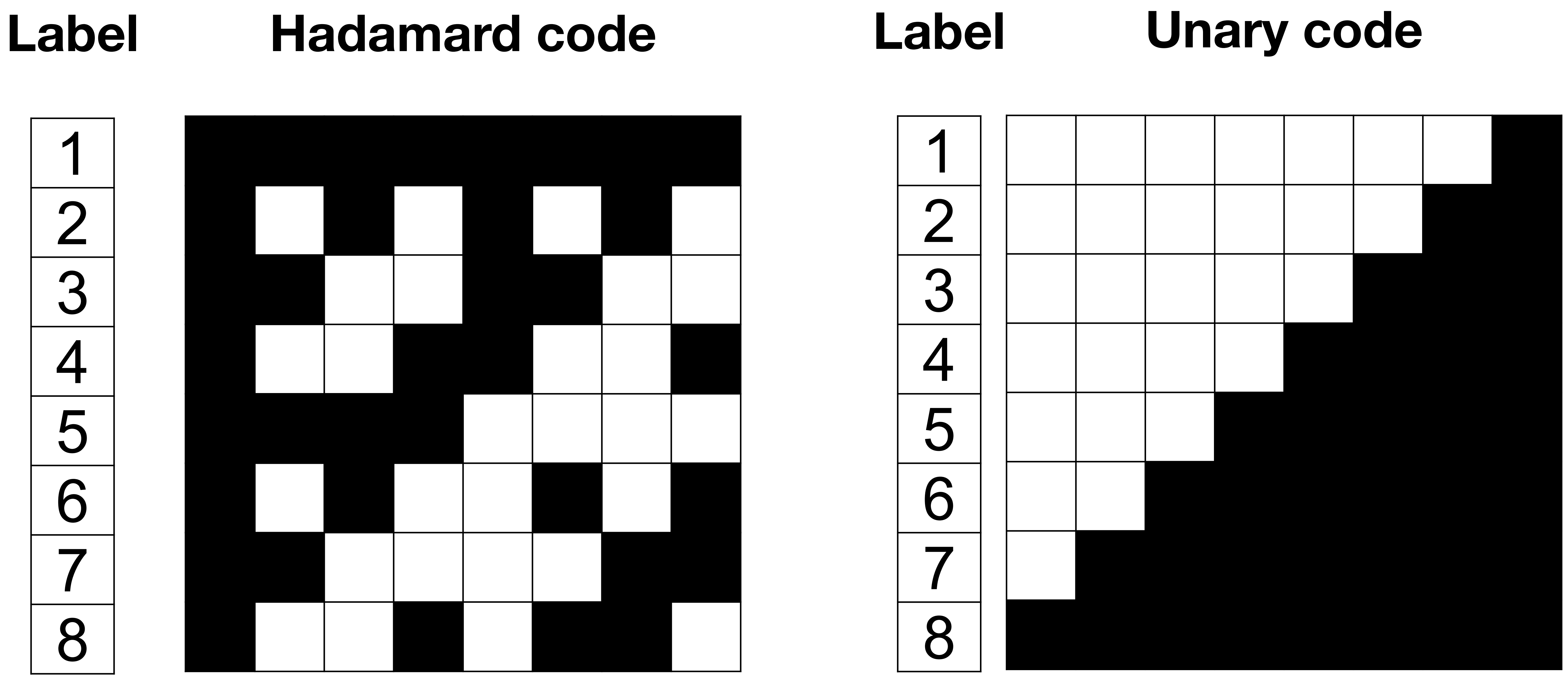
Error-correction capability

Label	Hadamard code	Unary code
		

	Hadamard code	Unary code
Hamming Distance	**4**	**1**
Classification Error	**~50%**	**~2%**

Encoding Design - Key Insight (2)

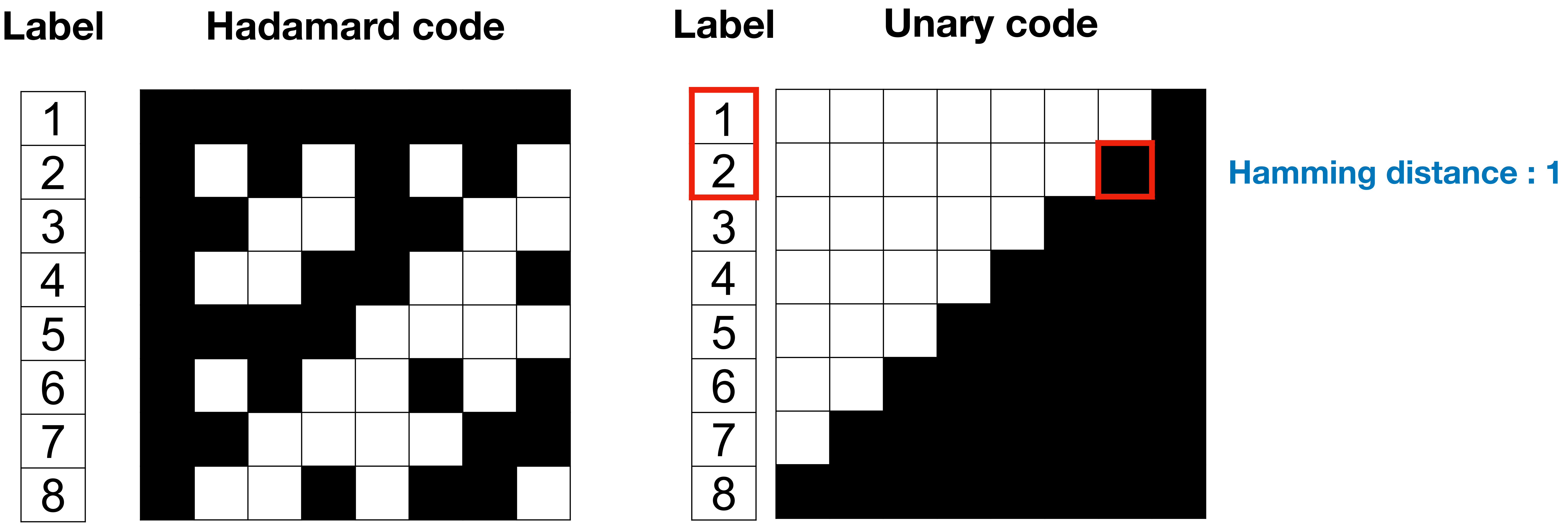
Regression objective : ↓ | Predicted value - Target value |



Encoding Design - Key Insight (2)

Regression objective : ↓ | Predicted value - Target value |

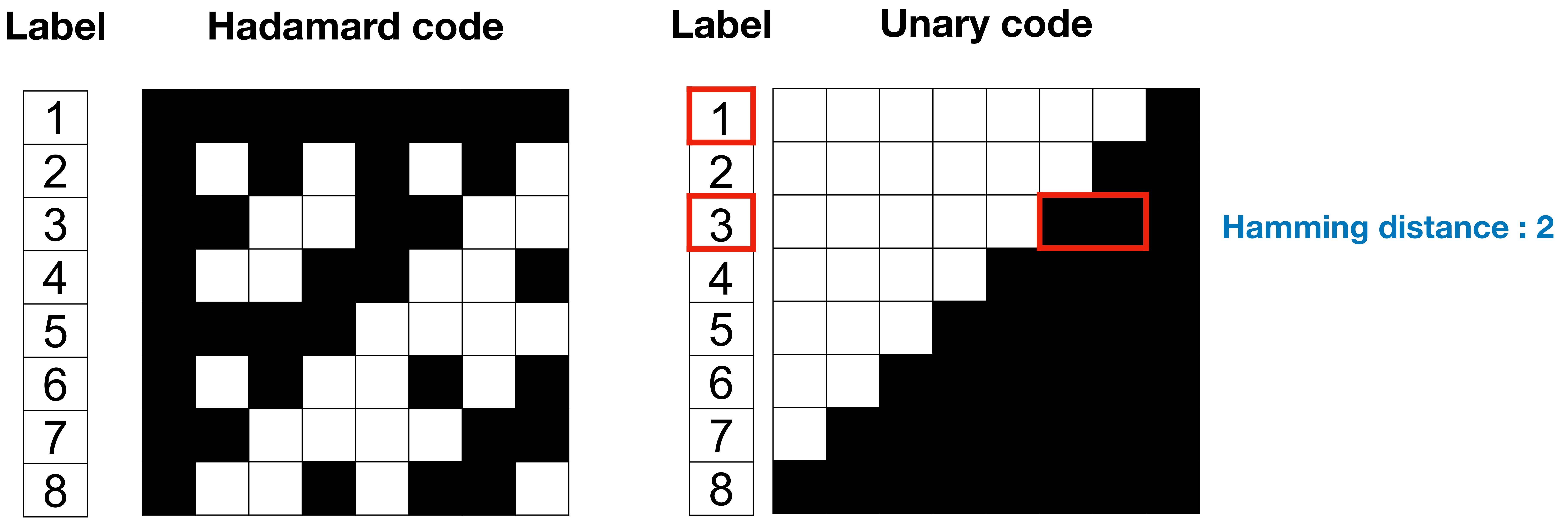
The hamming distance between two codes should increase with the difference between corresponding label values.



Encoding Design - Key Insight (2)

Regression objective : ↓ **| Predicted value - Target value |**

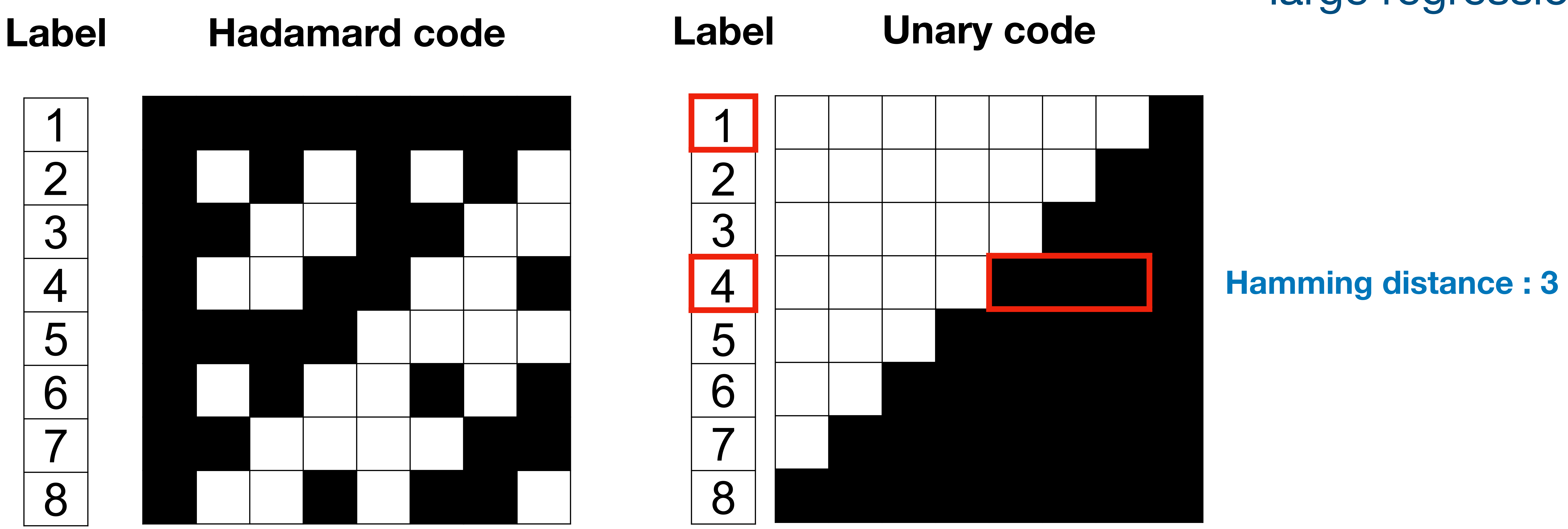
The hamming distance between two codes should increase with the difference between corresponding label values.



Encoding Design - Key Insight (2)

Regression objective : ↓ | Predicted value - Target value |

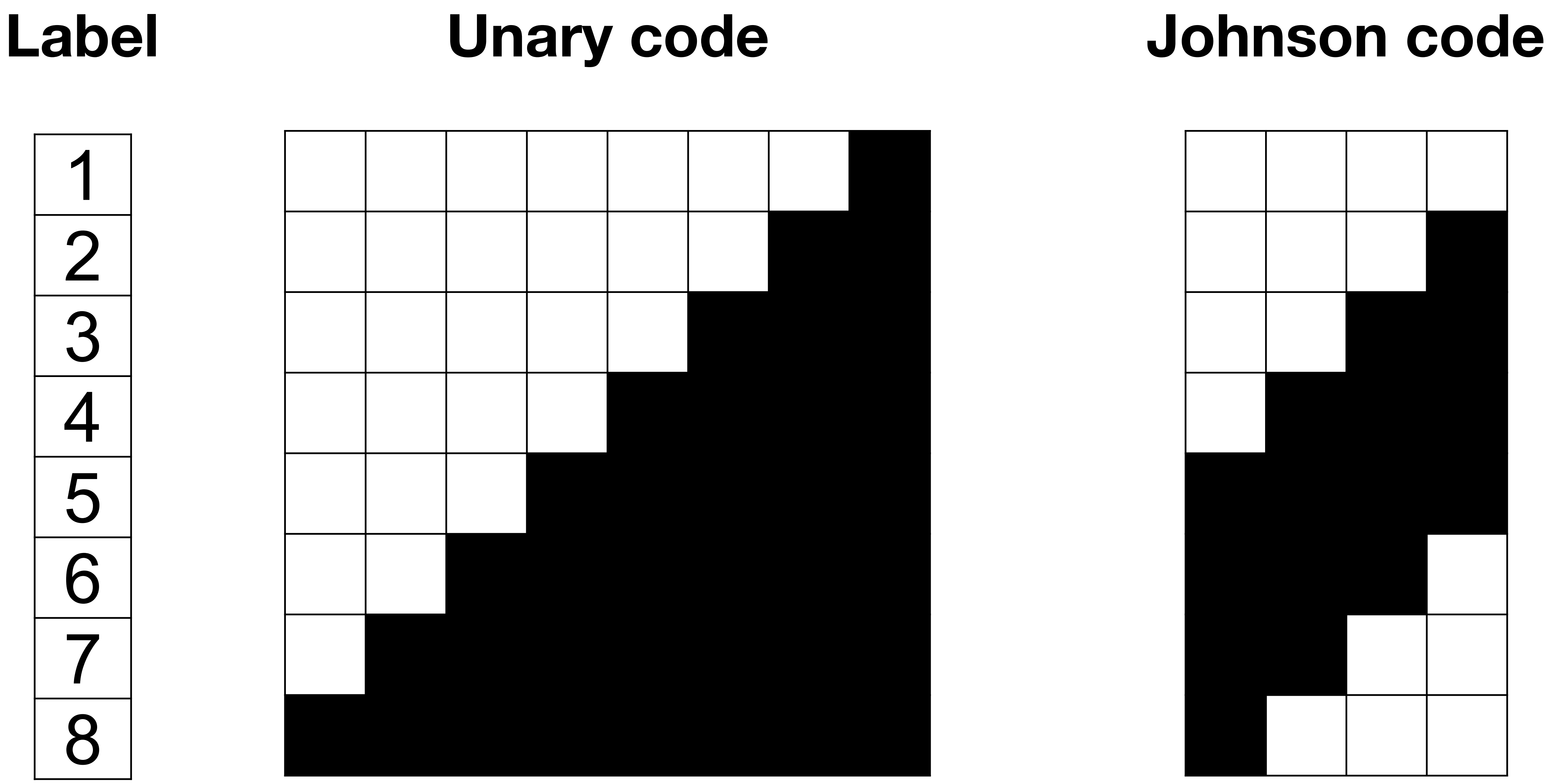
The hamming distance between two codes should increase with the difference between corresponding label values. → Reduces the probability of making large regression errors.

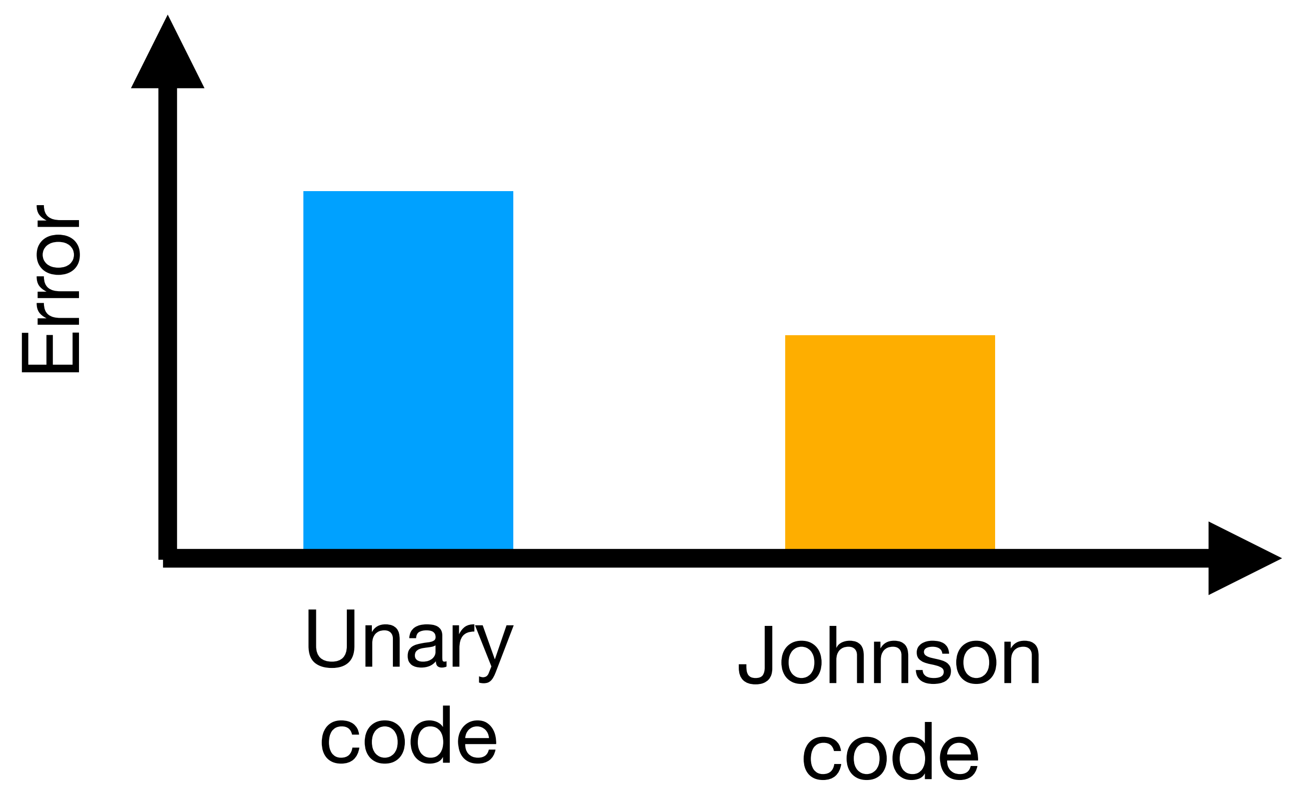


Unary code follows this property and results in lower regression error than Hadamard code.

Encoding Design - Key Insight (3)

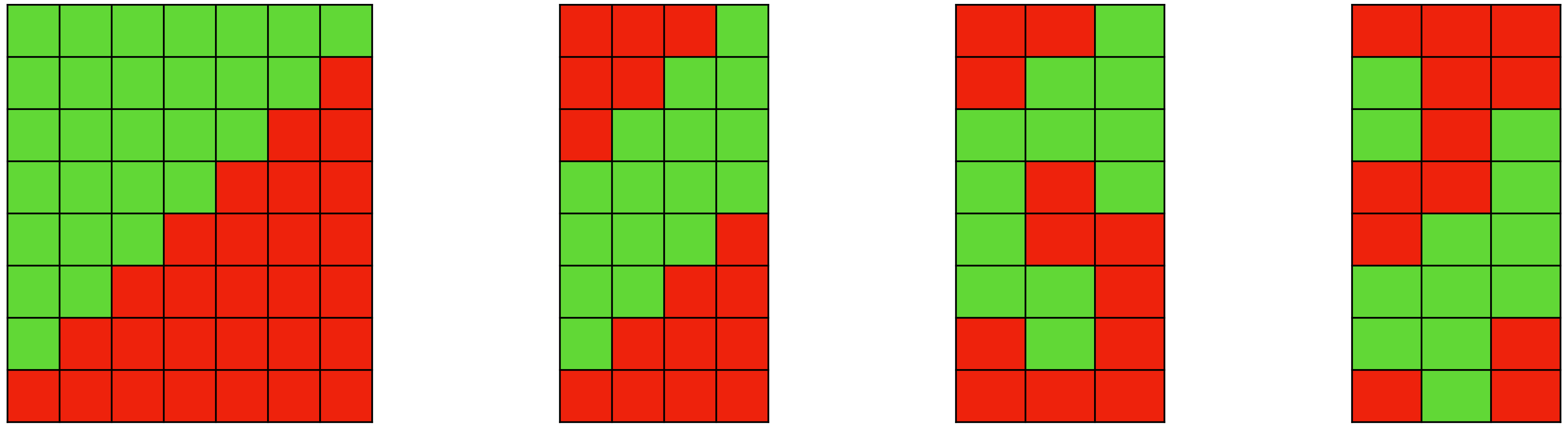
Classifiers' nonuniform error probability distribution can be exploited to design better and more compact codes.



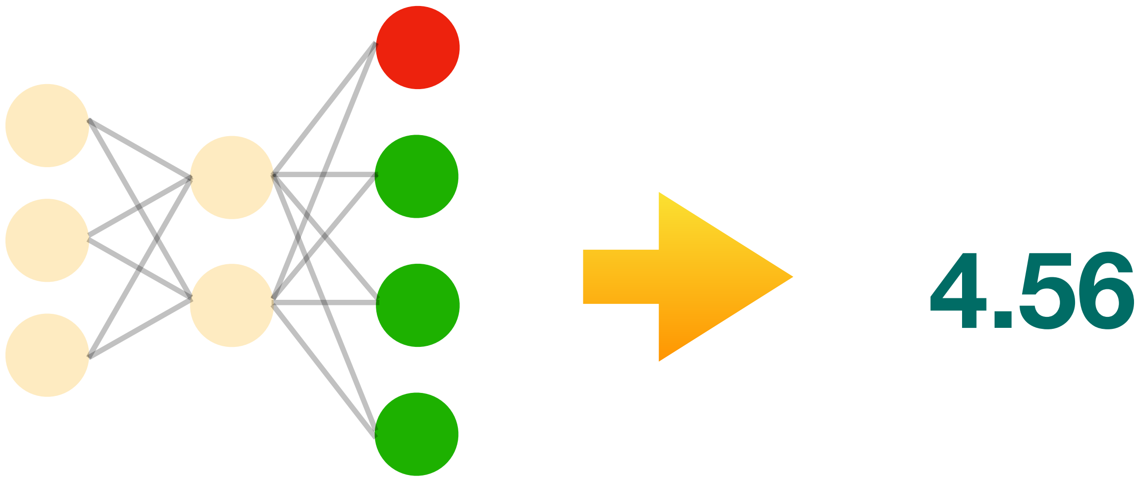


BEL Design Parameters

- Encoding functions



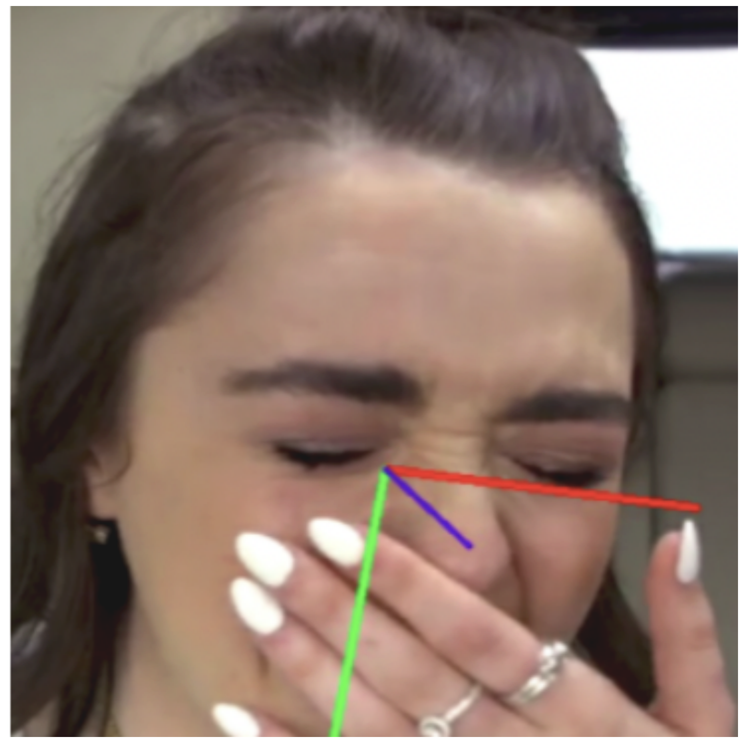
- Decoding functions



- Loss functions

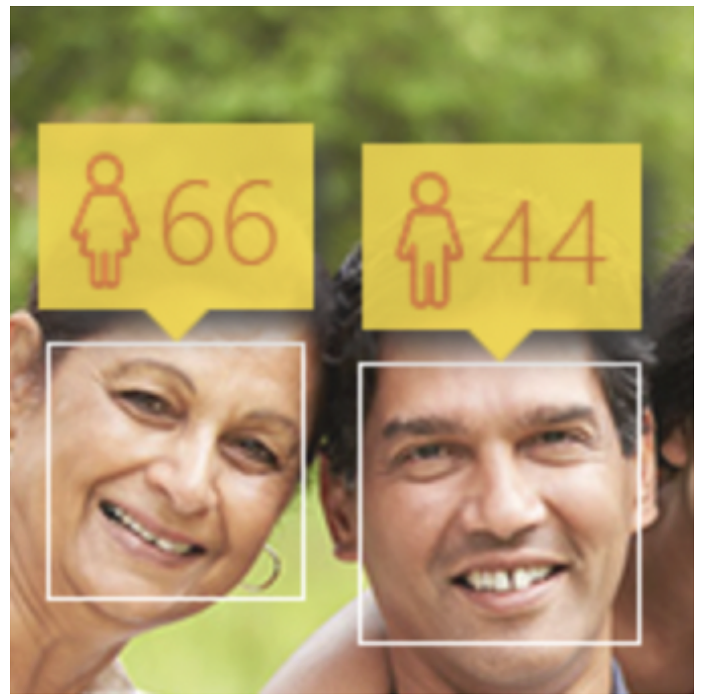
$$\mathcal{L}(Y, \hat{Y})$$

Evaluation



Head pose estimation

Facial landmark detection



Age estimation

End-to-end autonomous driving

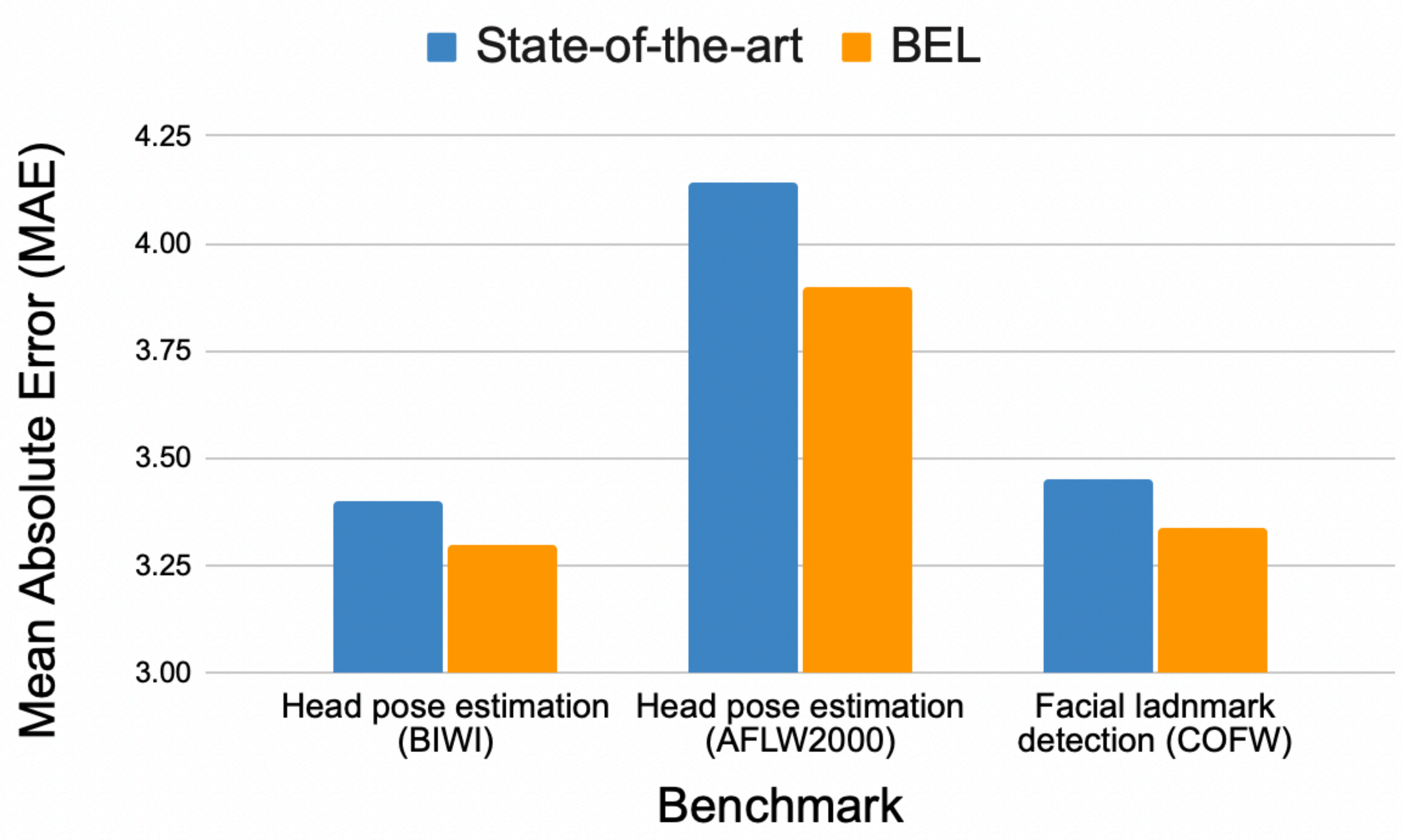
Image sources:

1. https://github.com/natanielruiz/deep-head-pose
2. D. Merget, M. Rock and G. Rigoll, "Robust Facial Landmark Detection via a Fully-Convolutional Local-Global Context Network," *CVPR* 2018
3. https://techxplore.com/news/2015-05-microsoft-age-estimate-tool-unleashed-real-time.html
4. https://www.idtechex.com/en/research-article/how-close-are-we-to-autonomous-cars/19191

Evaluation

10% lower error than direct regression

7.2% lower error than specialized approaches



Check our paper for more information!

https://github.com/ubc-aamodt-group/BEL_regression