Eye-Movement Patterns and Viewing Biases During Visual Scene Processing

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Outline

1. Visual attention
2. Influence of Age
3. The instructive case of ASD people
4. Predicting saliency on paintings
5. Conclusion

Visual attention
Presentation
Overt vs covert
Bottom-Up vs Top-Down
Bottom-Up models of overt attention
Influence of Age
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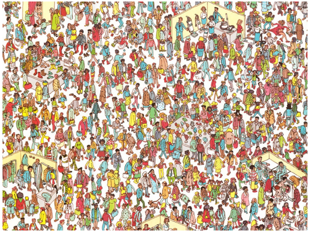
Introduction to visual attention (1/4)

Natural visual scenes are cluttered and contain many different objects that cannot all be processed simultaneously.



Where is Waldo, the young boy wearing the red-striped shirt...

Amount of information coming down the optic nerve $10^8 - 10^9$ bits per second

Far exceeds what the brain is capable of processing...

Introduction to visual attention (2/4)

Visual attention

Posner proposed the following definition (Posner, 1980). Visual attention is used:

- to select important areas of our visual field (alerting);
- to search for a target in cluttered scenes (searching).

There are several kinds of visual attention:

- Overt visual attention: involving eye movements;
- Covert visual attention: without eye movements (Covert fixations are not *easily* observable).

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Introduction to visual attention (3/4)

Bottom-Up vs Top-Down

- Bottom-Up: some things draw attention reflexively, in a task-independent way (Involuntary; Very quick; Unconscious);


- Top-Down: some things draw volitional attention, in a task-dependent way (Voluntary; Very slow; Conscious).

Introduction to visual attention (3/4)

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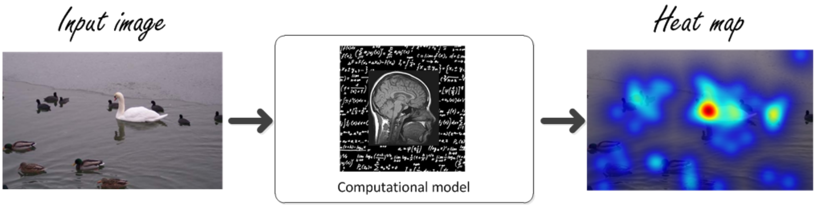
Introduction to visual attention (4/4)

Computational models of visual attention aim at predicting where we look within a scene.

Bottom-Up models of overt attention



From handcrafted models to deep models (1/3)

- Handcrafted models:
  - Itti (Itti et al., 1998), LeMeur (Le Meur, 2005, Le Meur et al., 2006), GBVS (Harel et al., 2006), Rare2012 (Riche et al., 2013)....
- Deep models:
  - DeepGaze (Kümmerer et al., 2014), MLNET (Cornia et al., 2016), Salicon (Huang et al., 2015), SalGan (Pan et al., 2017)...

Many progresses have been done in many aspects (e.g., datasets, eye-tracking expe., metrics...)

.... but some important points have been so far overlooked ....

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➟ Important aspects of our visual system are clearly overlooked:

- Current models implicitly assume that eyes are equally likely to move in any direction;
- Viewing biases are not taken into account (except the central bias);
- The temporal dimension is not considered (static saliency map) $\Rightarrow$ saccadic models (Boccignone and Ferraro, 2004, Clarke et al., 2017, Le Meur and Coutrot, 2016, Le Meur and Liu, 2015);
- The peculiarities of observers are not considered, Universal vs Personalized saliency map??

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From handcrafted models to deep models (3/3)

In this presentation, I aim to push forward the idea that we have to change the current paradigm when designing attention model:

- From Universal to Personalized
- From Agnostic to Observer / Content -aware
- From Static to Dynamic (not presented, see (Le Meur and Coutrot, 2016, Le Meur and Liu, 2015))

- Le Meur et al. (2017). *Visual attention saccadic models learn to emulate gaze patterns from childhood to adulthood*. IEEE Transactions on Image Processing, 26(10), 4777-4789.
- Le Meur et al. (2020). *From Kanner Autism to Asperger Syndromes, the Difficult Task to Predict Where ASD People Look at*. IEEE Access, 8, 162132-162140.
- Le Meur et al. (2020). *Can we accurately predict where we look at paintings?*. Plos one, 15(10), e0239980.

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Influence of age on the gaze pattern (1/4)

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Materials and methods of eye-tracking experiment conducted by (Helo et al., 2014):

- 101 subjects, 23 adults and 78 children divided into 5 groups: 2 y.o., 4-6 y.o., 6-8 y.o., 8-10 y.o. and adults group;
- Thirty color pictures taken from children books (10 seconds of viewing);
- Participants were instructed to explore the images.

(a) (b) (c) (d) (e)

Fig. 1. (a) Original stimulus; (b) and (c) represent fixation maps (red crosses indicate fixation) for 2 year-old and adult group, respectively; (d) and (e) represent the actual saliency maps for 2 year-old and adults groups, respectively.

Le Meur et al. (2017), Visual attention saccadic models learn to emulate gaze patterns from childhood to adulthood, IEEE Trans. Image Processing.

Influence of age on the gaze pattern (2/4)

We evaluate ten handcrafted (unsupervised) saliency models:

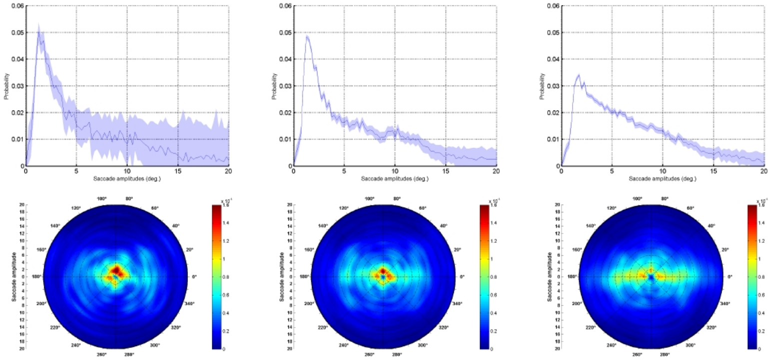
- ➟ Significant influence of bottom-up factors for all age groups;
- ➟ Significant main effect of age (ANOVA) on models' performance;
- ➟ Post-hoc Bonferroni comparisons show significant differences between all age groups, except between adults and 6-10 y.o., and between 4-6 y.o. and 2 y.o.;
- ➟ The best match is obtained for the 6-10 y.o. group.

Those differences are due to the maturation of our visual system

Le Meur et al. (2017), Visual attention saccadic models learn to emulate gaze patterns from childhood to adulthood, IEEE Trans. Image Processing.

Influence of age on the gaze pattern (3/4)

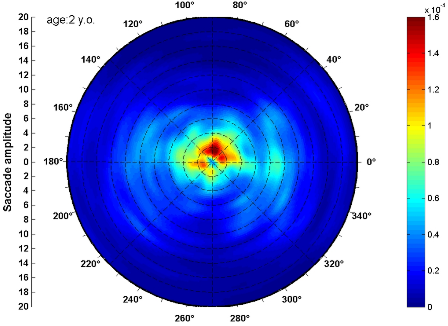
- Saccade amplitudes increase with age while fixation durations decrease with age;
- A strong horizontal bias in the adult group;
- A strong center bias for young children.

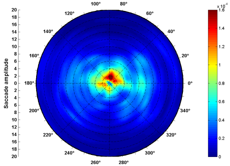


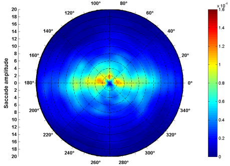
(a) 2 year-old (b) 4-6 year-old (c) Adults

Fig. 4. Distribution of saccade amplitudes (top row) and polar plots of joint distribution of saccade amplitudes and orientations (bottom row) for different age groups: (a) 2 year-old group to (d) adult group. The light blue envelope on top-row curves represents the standard error of the mean, amplified by a factor of 2000. The 6-8 and 8-10 year-old distributions are not displayed for the sake of clarity. They are available in the supplementary materials.

Influence of age on the gaze pattern (4/4)

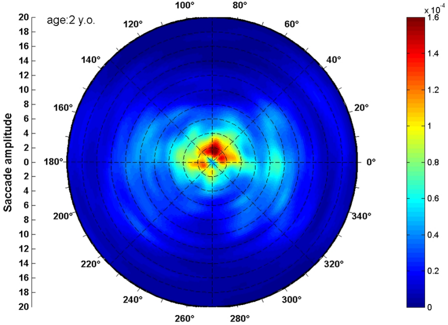


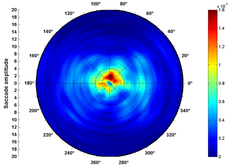


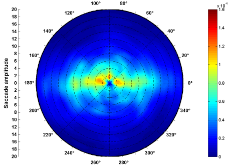


Tailoring saccadic models with this prior knowledge improve the relevance of the prediction and the overall performance (see (Le Meur et al., 2017))

Influence of age on the gaze pattern (4/4)







Tailoring saccadic models with this prior knowledge improve the relevance of the prediction and the overall performance (see (Le Meur et al., 2017))

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The instructive case of ASD people (1/6)

Modelling the visual attention of people with autism spectrum disorder (ASD) is attracting more and more interest:

- for determining where ASD people look (Duan et al., 2019a, Nebout et al., 2019, Wei et al., 2019);
- for inferring the visual features influencing the gaze deployment (Jiang and Zhao, 2017).

In a recent study (Le Meur et al., 2020), we ask two questions:

1. Do existing neurotypical saliency models able to predict where ASD people look at?
2. Do ASD saliency models generalize well?

Le Meur et al., From Kanner Autism to Asperger Syndromes, the Difficult Task to Predict Where ASD People Look at. IEEE Access, 8, 162132-162140.

The instructive case of ASD people (2/6)

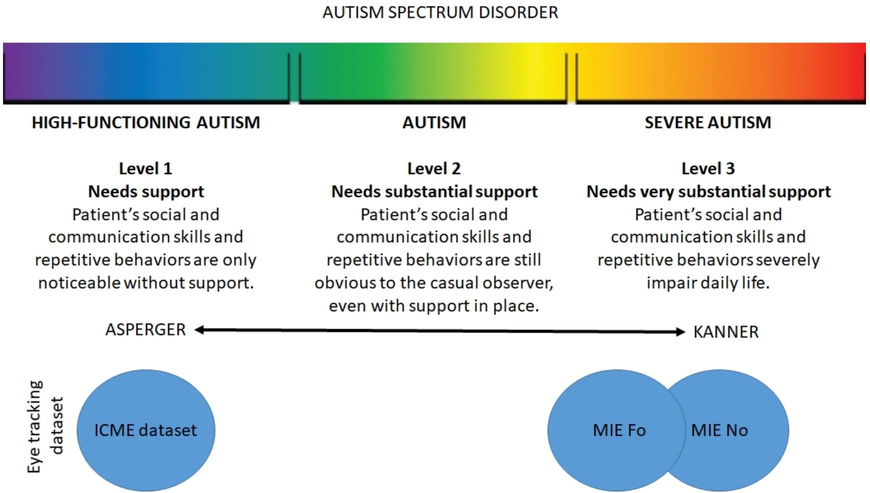
Eye-tracking experiments involving ASD subjects:

- Dataset from (Duan et al., 2019b), called ICME, 14 observers, 300 images;
- Datasets from (Le Meur et al., 2020), called MIE Fo and MIE No, 17/12 observers, 25 images.

FIGURE 1. **Sample images used for ICME eye tracking test (top row) and for MIE Fo and MIE No eye tracking test (bottom row).**

All data are available on the following link
https://www-percept.irisa.fr/asperger_to_kanner/.

The instructive case of ASD people (3/6)



The instructive case of ASD people (4/6)

We evaluate 6 saliency models over the three datasets:

- 5 deep models trained with eye tracking data involving neurotypical observers:
  - SAM-ResNet/VGG (Cornia et al., 2018), SalGAN (Pan et al., 2017), DeepGazeII (Kümmerer et al., 2016), MLNET (Cornia et al., 2016).
- 1 deep model (Nebout's model) trained with ICME dataset (Nebout et al., 2019)

8 metrics are used to evaluate models' performance:

- CC, IG, KL, NSS, SIM, AUC-(B,J,S) (Bylinskii et al., 2018, Le Meur and Baccino, 2013)

The instructive case of ASD people (5/6)

TABLE 4. Performances over ASD datasets of neurotypical deep models and one dedicated model. Best scores are shown in bold, and standard deviation in brackets.

Dataset	Model	CC ↑	IG ↑	KL ↓	NSS ↑	SIM ↑	AUC-B ↑	AUC-J ↑	AUC-S ↑
ICME	Nebout	0.69 (0.11)	**-1.74 (0.88)**	**1.02 (0.56)**	1.25 (0.38)	**0.66 (0.05)**	**0.77 (0.05)**	0.79 (0.04)	0.61 (0.08)
	SAM-Resnet	0.72 (0.13)	-4.60 (2.50)	3.17 (1.88)	1.49 (0.54)	0.63 (0.07)	0.74 (0.06)	0.79 (0.05)	**0.66 (0.07)**
	SAM-VGG	0.60 (0.14)	-4.76 (2.61)	3.37 (2.00)	1.32 (0.58)	0.55 (0.06)	0.66 (0.06)	0.78 (0.05)	0.61 (0.06)
	SalGAN	0.68 (0.13)	-2.02 (1.29)	1.37 (0.96)	1.41 (0.47)	0.62 (0.06)	0.74 (0.05)	0.79 (0.05)	**0.66 (0.06)**
	DeepGaze II	**0.73 (0.15)**	-2.44 (1.67)	1.63 (1.25)	**1.51 (0.59)**	0.65 (0.08)	0.73 (0.07)	**0.81 (0.05)**	0.63 (0.08)
	MLNET	0.60 (0.17)	-1.95 (1.01)	1.25 (0.67)	1.32 (0.66)	0.59 (0.06)	0.68 (0.06)	0.79 (0.06)	0.62 (0.07)
MIE Fo	Nebout	**0.66 (0.09)**	-2.74 (1.28)	1.53 (0.86)	1.41 (0.43)	**0.59 (0.04)**	**0.77 (0.04)**	0.79 (0.04)	0.58 (0.06)
	SAM-Resnet	0.63 (0.14)	-2.83 (1.55)	1.54 (1.00)	1.39 (0.55)	**0.59 (0.06)**	0.70 (0.08)	0.79 (0.04)	**0.63 (0.06)**
	SAM-VGG	0.58 (0.16)	-2.99 (1.26)	1.67 (0.85)	1.35 (0.62)	0.56 (0.06)	0.69 (0.07)	0.79 (0.04)	0.60 (0.05)
	SalGAN	0.62 (0.14)	-2.23 (0.98)	1.21 (0.62)	1.39 (0.54)	0.58 (0.06)	0.76 (0.05)	0.79 (0.04)	0.62 (0.06)
	DeepGaze II	0.63 (0.15)	-2.70 (1.16)	1.57 (0.81)	**1.46 (0.59)**	**0.59 (0.06)**	0.72 (0.025)	**0.80 (0.04)**	0.59 (0.07)
	MLNET	0.47 (0.19)	**-1.99 (0.66)**	**0.99 (0.40)**	1.08 (0.62)	0.52 (0.08)	0.69 (0.07)	0.75 (0.07)	0.60 (0.06)
MIE No	Nebout	**0.50 (0.14)**	-3.70 (2.43)	1.97 (1.62)	**1.39 (0.56)**	**0.47 (0.09)**	**0.78 (0.07)**	**0.80 (0.07)**	**0.57 (0.10)**
	SAM-Resnet	0.29 (0.12)	-4.35 (2.73)	2.39 (1.81)	0.81 (0.40)	0.37 (0.07)	0.70 (0.09)	0.73 (0.08)	0.51 (0.08)
	SAM-VGG	0.24 (0.13)	-4.82 (3.17)	2.80 (2.05)	0.70 (0.46)	0.33 (0.06)	0.62 (0.09)	0.73 (0.08)	0.52 (0.07)
	SalGAN	0.29 (0.12)	**-3.34 (0.90)**	**1.83 (0.59)**	0.81 (0.41)	0.36 (0.07)	0.69 (0.09)	0.74 (0.08)	0.51 (0.09)
	DeepGaze II	0.35 (0.12)	-4.25 (2.18)	2.46 (1.68)	0.96 (0.42)	0.38 (0.09)	0.66 (0.08)	0.76 (0.06)	0.51 (0.07)
	MLNET	0.19 (0.12)	-3.45 (0.74)	**1.83 (0.52)**	0.50 (0.35)	0.31 (0.08)	0.62 (0.08)	0.68 (0.07)	0.51 (0.06)

The instructive case of ASD people (6/6)

Dataset	Model	CC ↑
ICME	Nebout	0.69 (0.11)
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	SalGAN	0.29 (0.12)
	DeepGaze II	0.35 (0.12)
	MLNET	0.19 (0.12)

Neurotypical models: average $CC = [0.66, 0.58, 0.27]$ for ICME, MIE Fo and MIE No, resp.

- Poor performance of neurotypical models on MIE Fo and MIE No;
- Severe drop in performance over MIE No (Kanner autism).
  $\Rightarrow$ **Lack of generalization**

ASD Model (Nebout's model (Nebout et al., 2019) trained over ICME):

- This model outperforms other models on MIEs datasets.
- More stable performances...

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Predicting saliency on paintings (1/5)

Eye-tracking experiments over Paintings:

- 21 observers, 150 paintings belonging to 5 art movements:

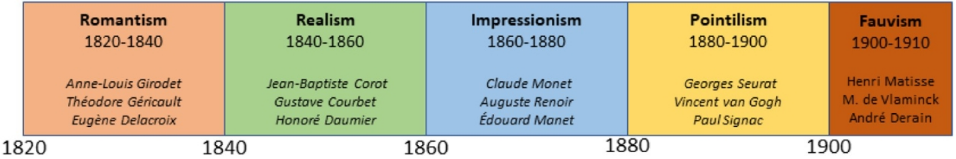

Fig 1. Main painting movements of 18^{th} and early 19^{th} century. The duration of each movement is approximately given. For each movement, we also give the name of some famous painters.

Goya (1812), Manet (1862), Bazille (1866), Dubois-Pillet (1885)

Le Meur et al. (2020), Can we accurately predict where we look at paintings?. Plos one, 15(10).

Predicting saliency on paintings (2/5)

- Visual scanpaths:

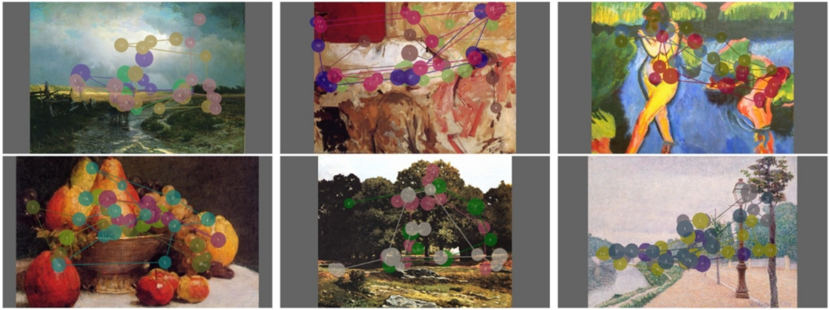

Fig 2. Examples of 4 scanpaths overlaid on paintings. The circles indicate the visual fixations. The number is the visual fixation index. From left to right: Vasilyev, *After a rain country road*, 1869; Sorolla, *Bacchante*, 1886; Pechstein, *Bank of a lake*, 1910; Fantin-Latour, *Bowl of fruits*, 1857; Sisley, *Chestnut avenue in la celle Saint Cloud*, 1865; Dubois-Pillet, *The Banks of the Seine at Neuilly, 1886.*

All data are available on the following link https://www-percept.irisa.fr/art_paintings/.

Predicting saliency on paintings (3/5)

➟ Joint distribution of saccade amplitudes and saccade orientations:

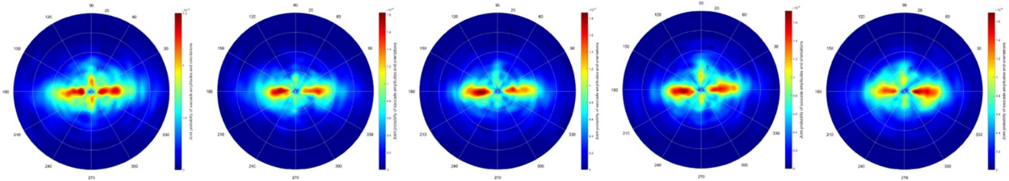

Fig 6. Joint distribution of saccade amplitudes and orientations for the five periods, e.g. Romanticism, Realism, Impressionism, Pointillism and Fauvism, are illustrated.

We observe no significant difference with gaze deployment over natural scenes.

Do computational models of visual attention predict well the salience of paintings?

Le Meur et al. (2020), Can we accurately predict where we look at paintings?. Plos one, 15(10).

Predicting saliency on paintings (4/5)

➠ Performance of saliency models:

Table 4. Performances of saliency models on paintings dataset.

	Model	CC ↑	KL ↓	SIM ↑	NSS ↑	AUC-B ↑	AUC-J ↑
Handcrafted models	GBVS	0.506	0.962	0.446	1.256	**0.809**	0.817
	RARE2012	0.443	1.020	0.438	1.103	0.777	0.786
	AIM	0.315	1.245	0.371	0.772	0.723	0.735
	AWS	0.427	1.045	0.430	1.083	0.762	0.769
	Mean	0.422	1.068	0.421	1.053	0.774	0.776
Deep models	MLNET	0.576	**0.832**	0.513	1.524	0.770	0.818
	DeepGazeII	0.485	0.896	0.488	1.394	0.679	0.804
	SALICON	0.538	0.880	0.517	1.445	0.708	0.827
	SAM-ResNet	**0.700**	0.984	**0.613**	**1.834**	0.782	**0.862**
	SAM-VGG	0.617	0.970	0.561	1.603	0.752	0.846
	Mean	0.583	0.912	0.551	1.560	0.738	0.831

https://doi.org/10.1371/journal.pone.0239980.t004

- Deep models perform better than handcrafted ones;
- Except SAM-ResNet, performances of deep models are not so good...
- On average, deep models perform better on ... Realism paintings.

Le Meur et al. (2020), Can we accurately predict where we look at paintings?. Plos one, 15(10).

Predicting saliency on paintings (5/5)

➠ Fine-tuning SAM-ResNet:

Table 6. Performances of SAM-ResNet after fine-tuning on the test dataset.

Model	**CC ↑**	**KL ↓**	**SIM ↑**	**NSS ↑**	**AUC-B ↑**	**AUC-J ↑**
SAM-ResNet	0.69	1.08	0.60	1.79	0.78	0.85
SAM-ResNet fine-tuned	0.75	0.83	0.68	1.92	0.84	0.88
Min.	0.58	0.33	0.56	1.30	0.76	0.81
Max.	0.89	3.00	0.77	2.72	0.89	0.92
Gain (%)	+9.7%	-23%	+11.8%	+7.2%	+7.5%	+2.9%

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- The fine-tuning increases the overall performance;
- A Gain of 9.7% on the correlation coefficient!

Le Meur et al. (2020), Can we accurately predict where we look at paintings?. Plos one, 15(10).

Outline

1. Visual attention
2. Influence of Age
3. The instructive case of ASD people
4. Predicting saliency on paintings
5. Conclusion

Conclusion

- First generation of attention model (handcrafted model);
- Second generation of attention model (deep-based model);
- Third generation (dynamic + observer/content-aware):
  - Saccadic model (from static to dynamic)
  - The key ingredients are observers and contents!
  - Viewing biases and observers-based tendency have to be identified!
  - Ecological eye-tracking experiments must be used to benchmark / train models.

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Thanks!!!