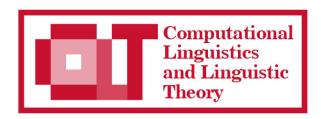
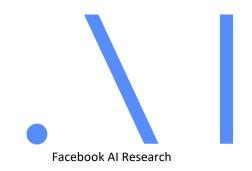
Is compositionality overrated? The view from language emergence

Marco Baroni CBMM Virtual Seminar June 2020









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Diane Bouchacourt



Roberto Dessì

Eugene Kharitonov



Outline

- Emergent language in deep networks: why, how, what?
- Compositionality and generalization in emergent languages
- Take-home messages

Deep networks do amazing things... but just one thing at a time!

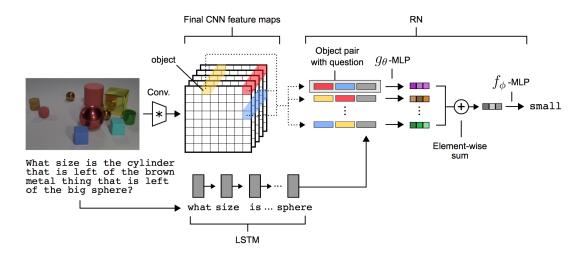






How can we harness their powers more flexibly?

Manual gluing?



\$ egrep '^a' in.txt | sort | uniq -c > out.txt

How can we harness their powers more flexibly?

- Manual gluing?
- Good Old AGI?



Wikipedia

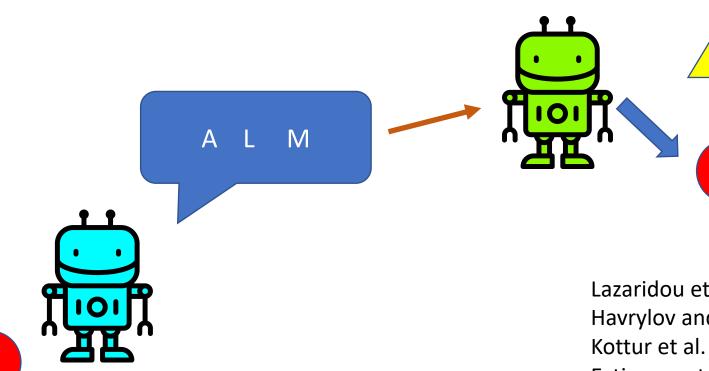
How can we harness their powers more flexibly?

- Manual gluing?
- Good Old AGI?
- Language!





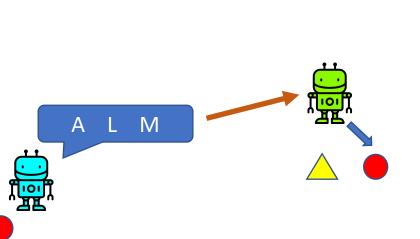
http://www.publicdomainfiles.com/



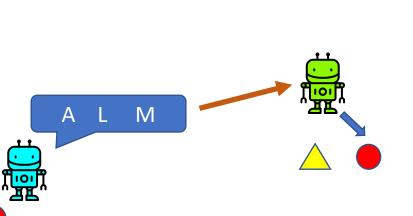
Lazaridou et al. ICLR 2017, Havrylov and Titov NIPS 2017, Kottur et al. EMNLP 2017, Evtimova et al. ICLR 2018,

...

3

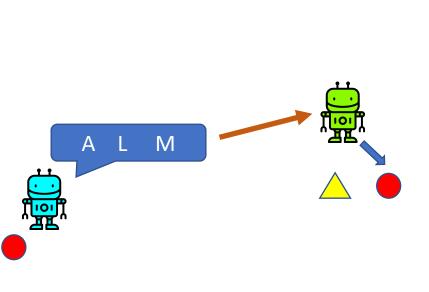


- Two networks must jointly solve a task
- Sender network sees some input (e.g., a target image) and sends a message to Receiver network
- Receiver gets some input, including Sender message, and performs an action (e.g., point to target image) to complete the task
- The message is a single discrete symbol or a sequence of discrete symbols from a fixed alphabet
- Networks rewarded for task success only,
 no supervision on the messages generated by Sender



this is the only way in which we constrain the emergent system to be human-language-like

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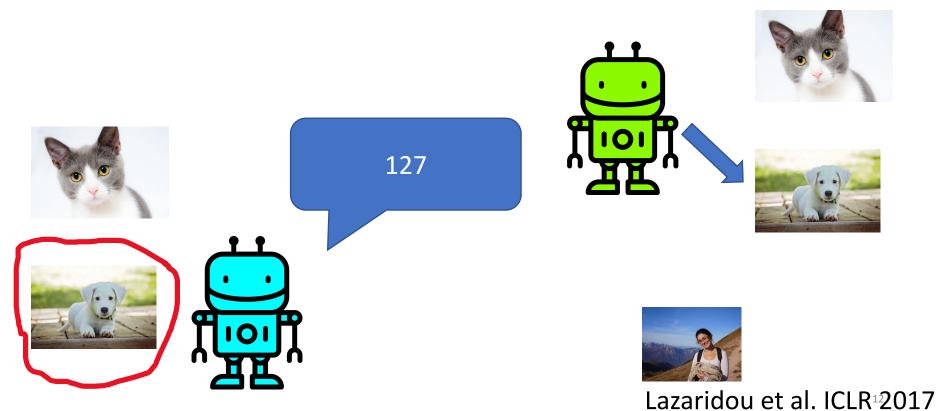


... because... where could we get the training data from?

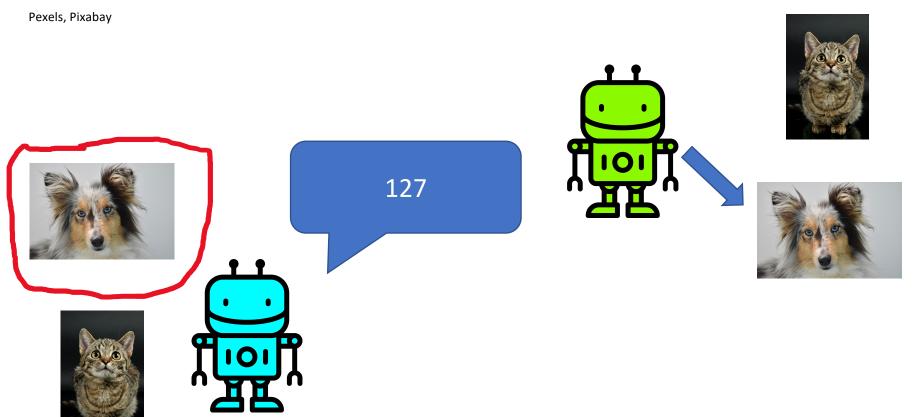
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The emergence of words

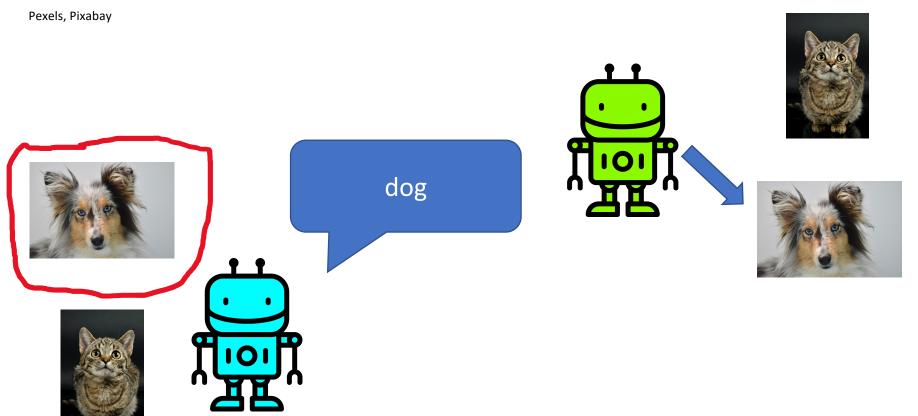
Pexels



The emergence of words

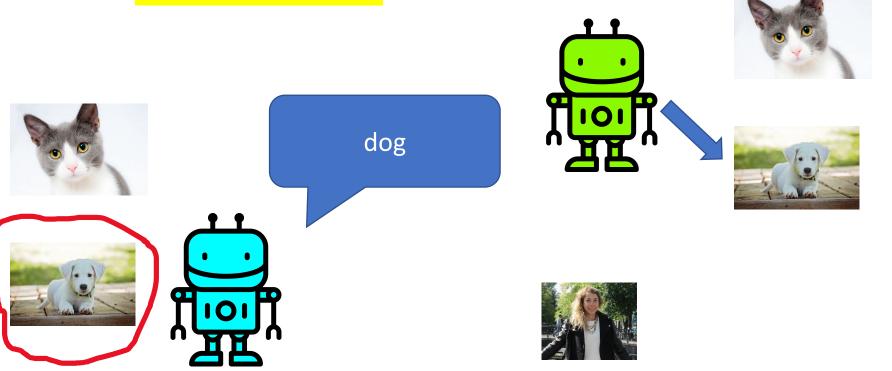


The emergence of words



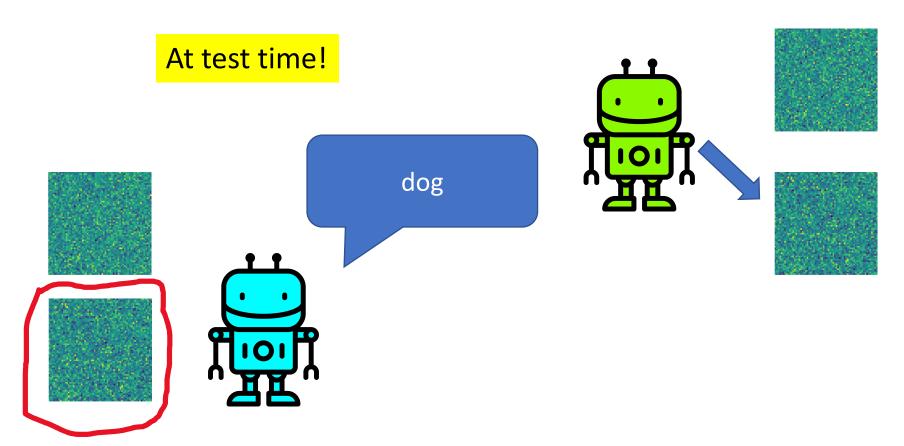
Emergent languages are tricky!

At training time...



Bouchacourt and Baroni EMNL₱ 2018

Emergent languages are tricky!

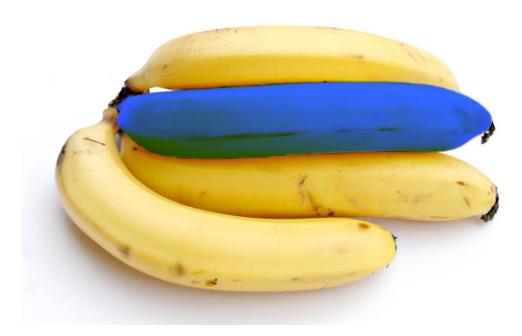


Outline

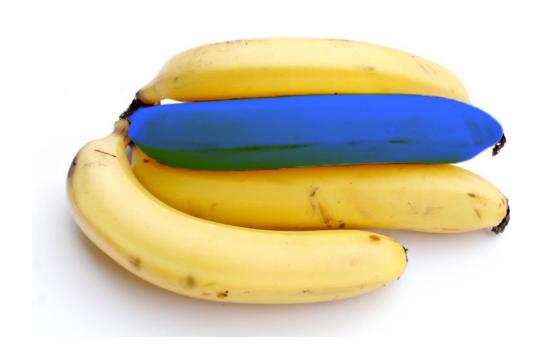
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Are emergent languages compositional?

Andreas ICLR 2019, Choi et al ICLR 2018, Havrylov & Titov NIPS 2017, Kottur et al EMNLP 2017, Mordatch & Abbeel AAAI 2018, Resnick et al AAMAS 2020...



Generalization



Compositionality and generalization

Train "banana" "blue"

Test



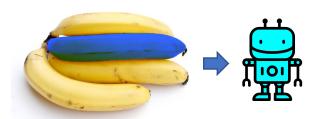
What makes an (emergent) language compositional?¹

¹ Where "compositional" is *not just a synonym* for: "able to generalize"

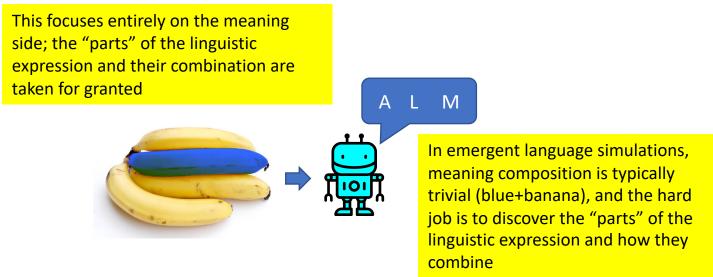
The meaning of a linguistic expression is a function of the meaning of its parts and the rules used to combine them (Boole, Frege, Montague, etc.)

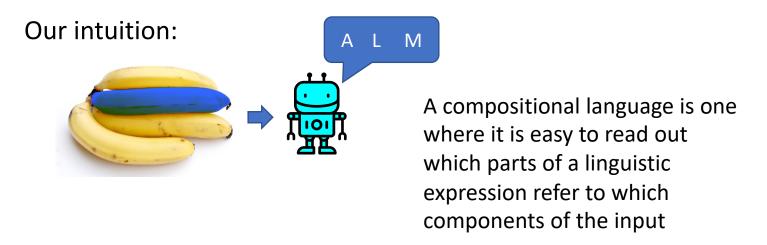
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This focuses entirely on the meaning side; the "parts" of the linguistic expression and their combination are taken for granted

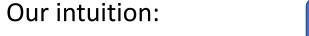


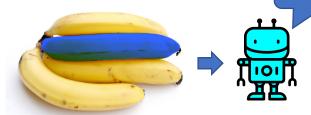
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M





A compositional language is one where it is easy to read out which parts of a linguistic expression refer to which components of the input

Compositional:

AL -> `blue'

M -> `banana'

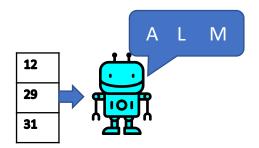
Less compositional:

AL -> `blue'

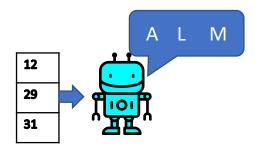
LM -> `banana'

Not compositional:
ALM -> `blue banana'

Applies when the only way to combine primitive input elements is to assemble them in a collection:

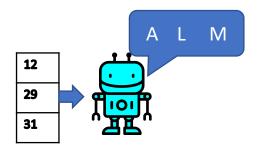


Applies when the only way to combine primitive input elements is to assemble them in a collection:



Examples: a list of attribute-value pairs (equivalently, a vector of values), a set of objects, a list of properties ('blue', 'banana'), ...

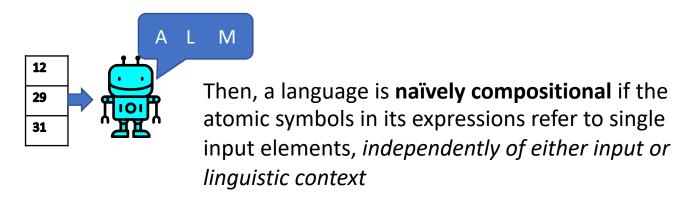
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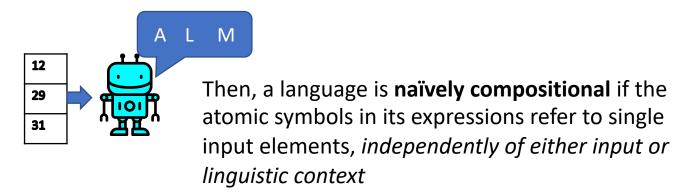
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90% of current emergent language simulations

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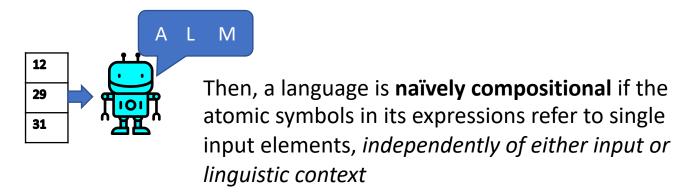


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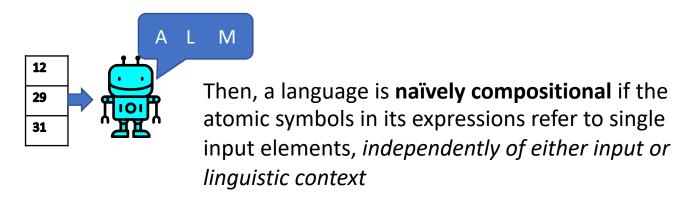
Such language is compositional because a collection of inputs will have to be expressed by the juxtaposition of the corresponding atomic symbols!

Applies when the only way to combine primitive input elements is to assemble them in a collection:



"Naïve" because it only considers ensembling as meaning composition function and atomic-symbol juxtaposition as form composition

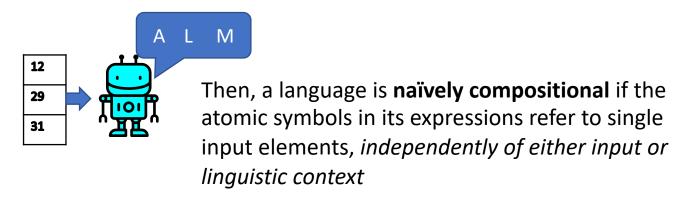
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This makes for an easy read-out of what is being composed!

Applies when the only way to combine primitive input elements is to assemble them in a collection:



Naïvely compositional: A -> 29 L -> 12 M -> 31

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Naïvely compositional:

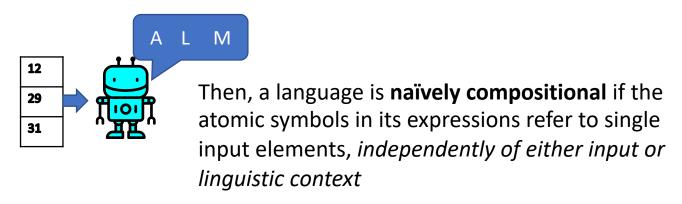
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bag-of-symbols or positional

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Non-compositional:

ALM -> [12,29,31]

Naïve compositionality

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Naïvely compositional:

A -> 29

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M -> 31

bag-of-symbols or positional

Non-compositional: ALM -> [12,29,31]

Non-naïvely compositional:

A -> 29 if immediately followed by L

L -> 12 if other input values are odd

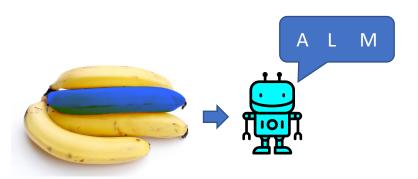
M -> 31 if one of previous symbols is A

Compositionality and generalization in emergent languages

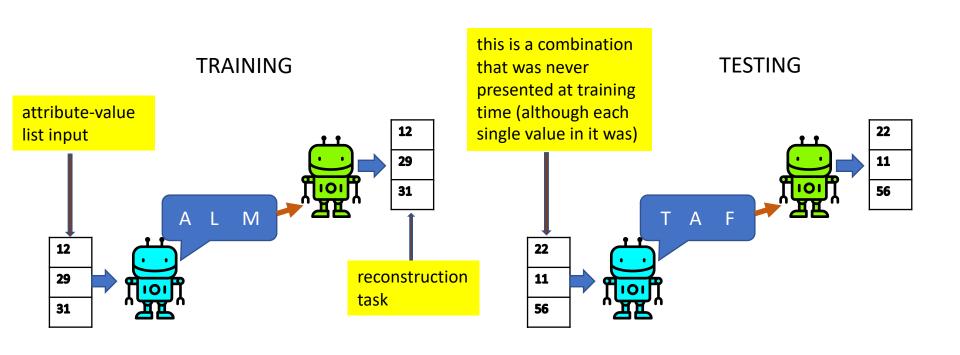


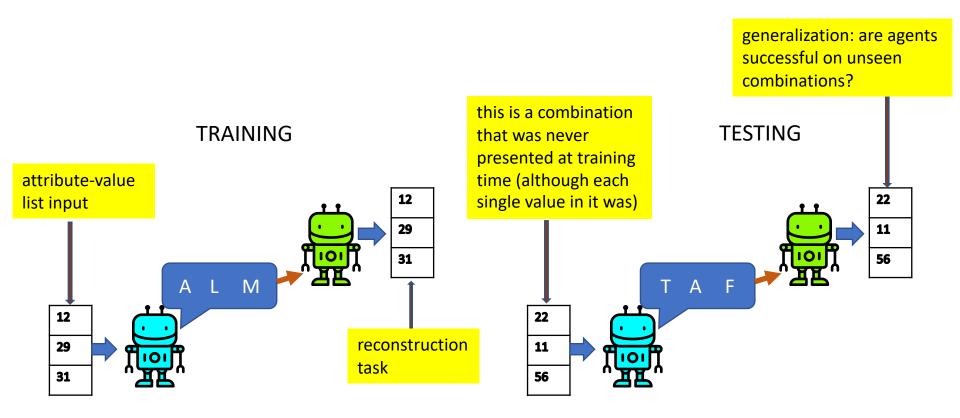


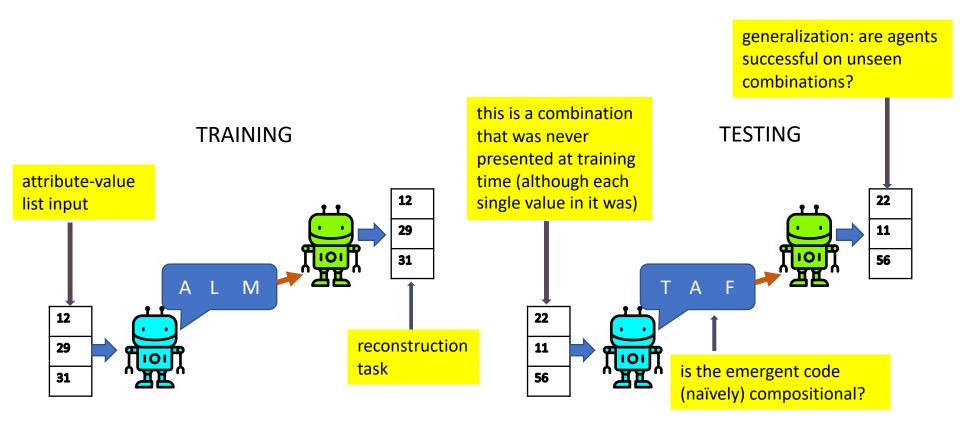
Chaabouni, Kharitonov et al. ACL 2020



attribute-value list input A L M reconstruction task

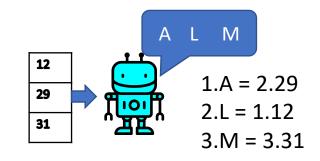






Quantifying (one type of) naïve compositionality

Positional disentanglement measures strong form of naïve compositionality: to what extent do symbols in a certain position univocally refer to different values of the same attribute



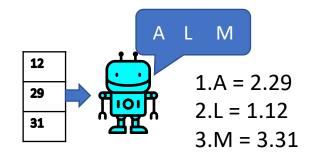
$$posdis = \frac{1}{c_{len}} \sum_{j=1}^{c_{len}} \frac{\mathcal{I}(s_j; a_1^j) - \mathcal{I}(s_j; a_2^j)}{\mathcal{H}(s_j)}$$

$$a_1^j = argmax_a \mathcal{I}(s_j; a); a_2^j = argmax_{a \neq a_1^j} \mathcal{I}(s_j; a)$$

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Similar results in experiments with other compositionality measures!

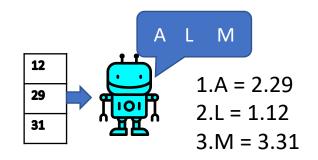
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Similar results in experiments with other compositionality measures!

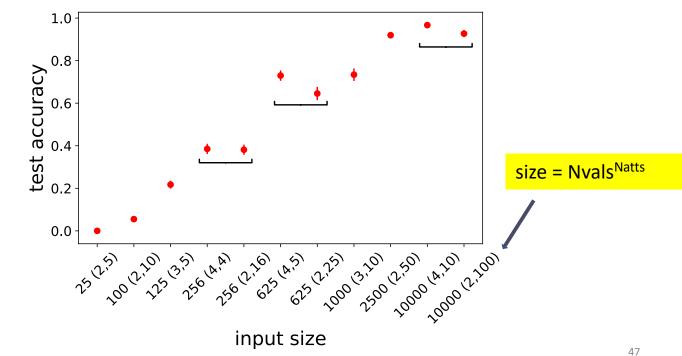
Still: to the extent that our emergent languages are compositional, they use positional encoding of information

Do emergent languages support generalization?

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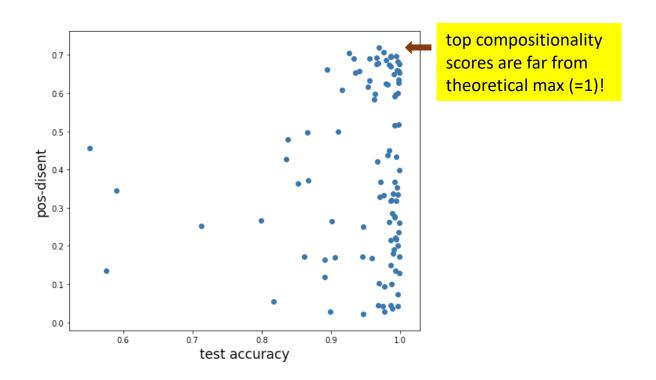
Yes, in function of how varied the training input is!

A general pearl of wisdom: do not test neural network generalization capabilities in small toy worlds!



Is compositionality needed for generalization?

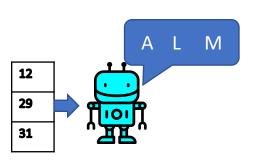
No!... no correlation between generalization and compositionality!



What's going on? "Leaky" compositionality

- Agents always need more expressive power to converge than would be strictly necessary in a perfectly compositional language
 - for 2 100-valued attributes in input, language needs at 3-symbol strings with 100-symbol vocabulary
 - Emergent languages are not "efficient" (Chaabouni et al NeurIPS 2019)
- The extra leeway is used by languages in non-compositional ways
 - E.g., in one of the most compositional languages, 2 symbols largely disambiguate the values of 2 attributes, but the 3d symbol is often needed to ``fine-tune'' the referent:
 - a c f -> 1.53 2.43
 - a -> 1.53 or 1.72
 - $c \rightarrow 2.43$
 - f -> 1.53 or 2.94

Interpretability, humans in the loop!



Easy:

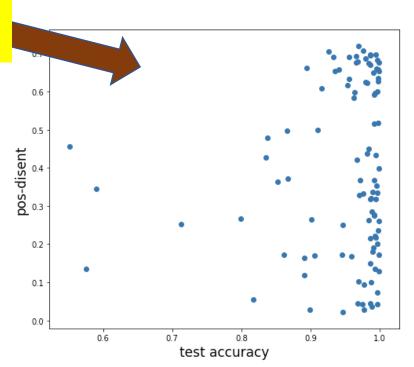
A in first position refers to value 12 of attribute 1

Hard:

A in first position and M in third refer to combination of 1.12 and 3.31 if second symbol is L, P or Q

It might not be necessary, but it appears to be sufficient for generalization

there's no highcompositionality, lowgeneralization language!



Compositional languages are "viral"!

- More compositional languages are easier for new Receivers (even Receivers with different architectures):
 - .87 Spearman correlation between compositionality and training speed of new Receivers with frozen Sender languages
 - .80 Spearman correlation between compositionality and generalization performance of new Receivers trained with frozen Sender languages
- We knew that cultural transmission favors the emergence of compositionality (iterated learning experiments: Kirby, Smith, etc.)
- It is also the case that compositionality favors cultural transmission!
- This is good, given that our end-goal is to breed large communities of interacting agents

Are compositional languages always the easiest to spread?

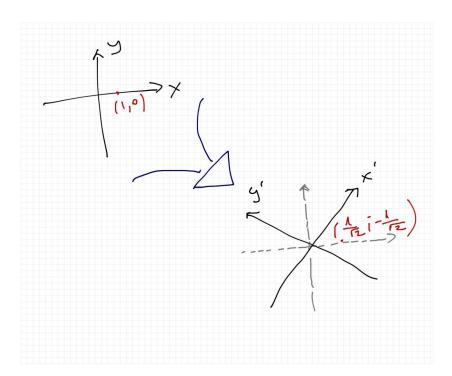
No! This will depend on the input (Lazaridou et al ICLR 2018), the task, and what comes easy to a neural network!



Kharitonov and Baroni: Emergent Language Generalization and Acquisition Speed are not Tied to Compositionality

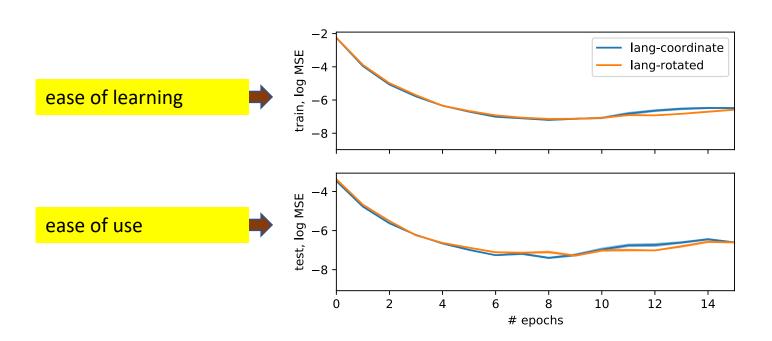
https://arxiv.org/abs/2004.03420

Coordinate and rotated languages

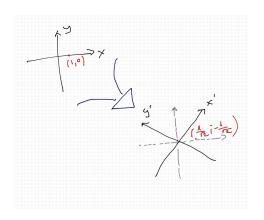


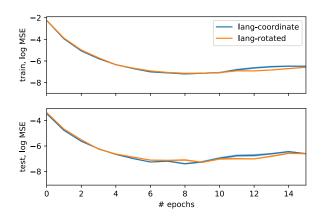
- Inputs: coordinates within unit circle
- Manually-crafted languages instead of trainable Sender
- Naïvely compositional "coordinate" language: two symbols directly corresponding to (discretized) coordinates
- "Rotated" language: symbols correspond to (discretized) coordinates after rotating the axes by $\pi/4$
 - Identifying either element always requires looking at both symbols, resulting in a very entangled encoding

Coordinate and rotated languages



Coordinate and rotated languages





- In the rotated language a linear transformation links (values denoted by) symbols and inputs
- Linear transformations are neural networks' favorite sport, so for Listener highly entangled rotated language is as easy as perfectly (naïve) compositional coordinate language
- There is nothing universal about more compositional languages being easier to learn and use!

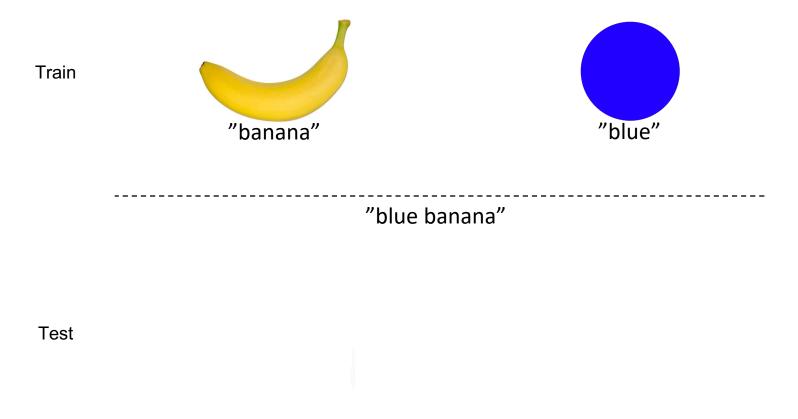
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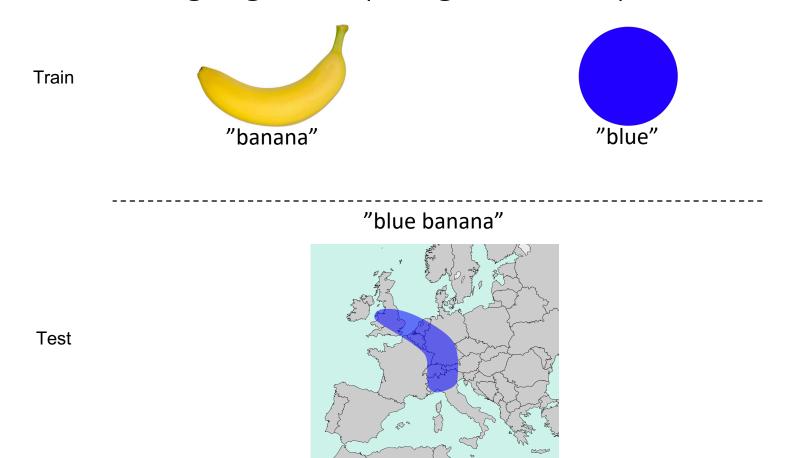
Take-home messages

- High-level program: evolve a shared language to empower communities of specialized neural networks
- Emergent neural network languages do tricky things
- Lots of work on emergent language compositionality, however:
 - No widely accepted, useful definition of compositionality
 - If what you want is generalization, ease of learning, viral strength, you might be better off focusing on optimizing those properties directly, without worrying about how "compositional" the emergent languages are
- But surely human language, the queen of communication systems, is very compositional?

Human language: the paragon of compositionality



Human language: the paragon of compositionality

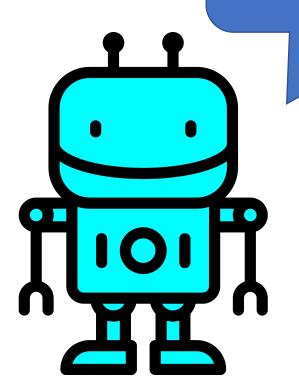


Blue banana communication

- Human language is full of non-compositional expressions: frozen metaphors, idioms, lexicalized constructions, ...
- It is not by chance that, 50 years into the Montagovian program, we are still only able to account for small fragments of English and other languages with a fully compositional semantics
- The right goal for emergent languages (and neural networks in general) might not be full compositionality, but a human-language-like opportunistic, efficient mixture of compositional and non-compositional means of expression



thankyou



https://github.com/facebookresearch/EGG