MULTI-AGENT COOPERATION AND THE EMERGENCE OF (NATURAL) LANGUAGE

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1줄 요약

1. Learning to communicate with *Referential games*

Overview

1. Learning to communicate with *Referential games*
    - passive learning is problematic in developing interactive machines
        - 에이전트 스스로 새로운 상황이나 파트너에 대해 이식이 가능한 언어를 개발할 수 있을까?

Overview

1. Learning to communicate with *Referential games*
    - passive learning is problematic in developing interactive machines

    - referential games between a sender & a receiver
        - most basic challenge
        - both agents observe two images
        - sender must send a symbol to the receiver
        - receiver recovers the target
        - both get a reward, if the receiver can refer the target

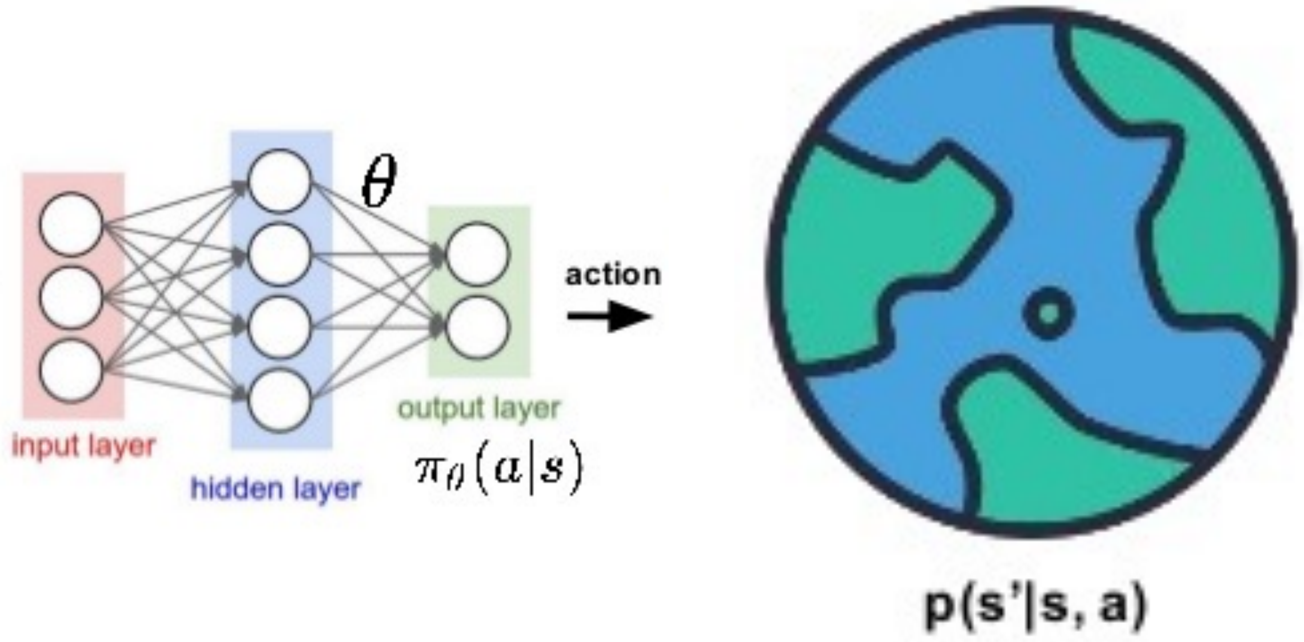
Overview

1. Learning to communicate with *Referential games*
    - passive learning is problematic in developing interactive machines
    - referential games between a sender & a receiver
    - agents may appear to learn even more meaningful concepts

Framework

1. There is a set of images represented by vectors $\{i_1, \ldots, i_N\}$, two images are drawn at random from this set, call them (i_L, i_R), one of them is chosen to be the "target" $t \in \{L, R\}$
2. There are two players, a sender and a receiver, each seeing the images - the sender receives input $\theta_S(i_L, i_R, t)$
3. There is a *vocabulary* V of size K and the sender chooses one symbol to send to the receiver, we call this the sender's policy $s(\theta_S(i_L, i_R, t)) \in V$
4. The receiver does not know the target, but sees the sender's symbol and tries to guess the target image. We call this the receiver's policy $r(i_L, i_R, s(\theta_S(i_L, i_R, t))) \in \{L, R\}$
5. If $r(i_L, i_R, s(\theta_S(i_L, i_R, t)) = t$, that is, if the receiver guesses the target, both players receive a payoff of 1 (win), otherwise they receive a payoff of 0 (lose).

Backgrounds

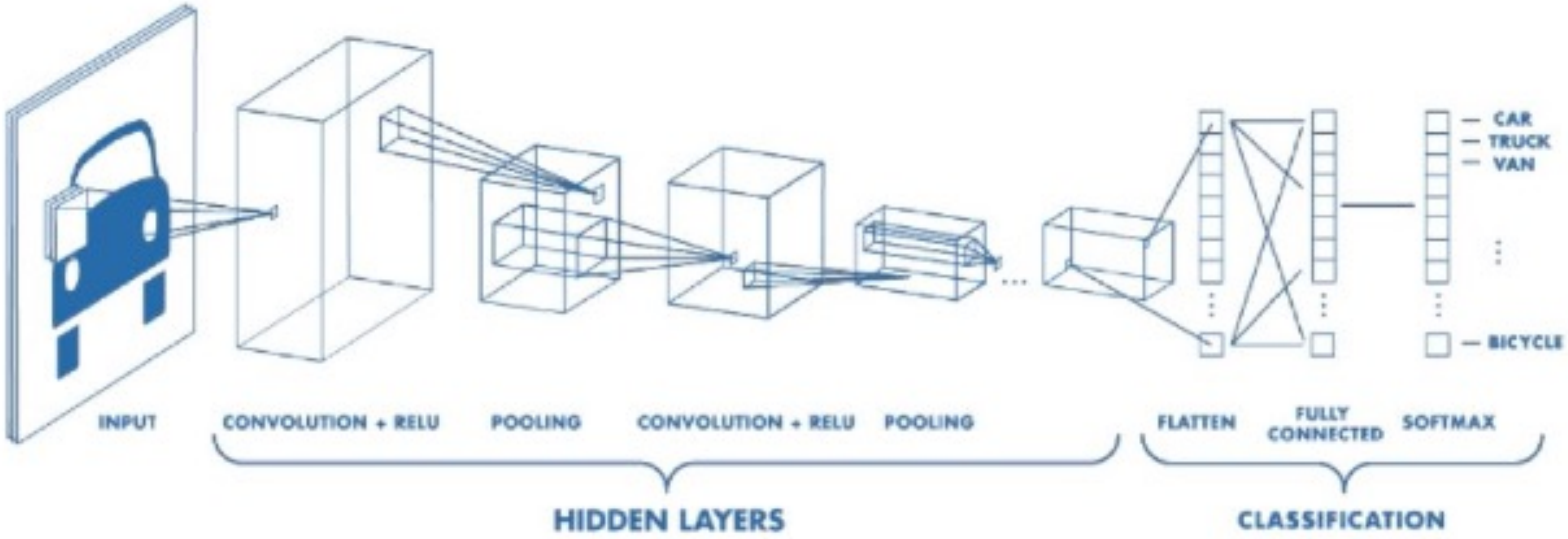


$$Update\ rule:\ \Delta\theta = \alpha * \nabla_\theta(log\pi(s,a,\theta))R(\tau)$$

Change in parameters

Learning rate

Backgrounds



Experimental Setup

- **Images**
  - McRae’s category
    - 463 base-level concrete concepts (e.g., cat, apple, car. . .) spanning across 20 general categories (e.g., animal, fruit/vegetable, vehicle. . .)
  - Randomly sample 100 images per concept from ImageNet(2009)
  - Pretrained VGG ConvNet(2014)
    - 4096-dim full-connected layer(*fc*)
    - 1000-dim softmax layer(*sm*)

Experimental Setup

- **Agents**

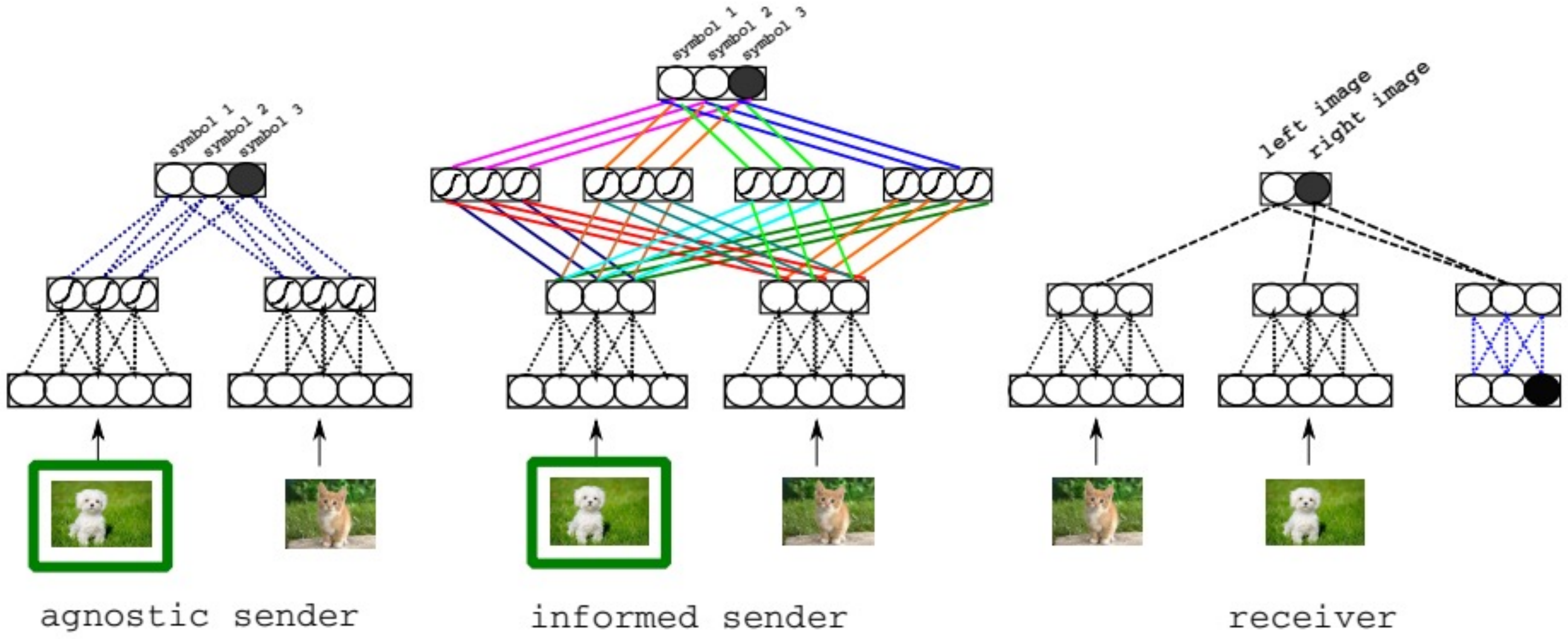


Figure 1: Architectures of agent players.

Experimental Setup

- **Training Details**
  - **embedding dim : 50**
  - **tested on two vocab sizes : 10 and 100 symbols**
  - **no weights are shared between agents**

  - 50K games with a batch-size 32

  - Reinforce rule (Williams, 1992)

Experiment1 – same-image game

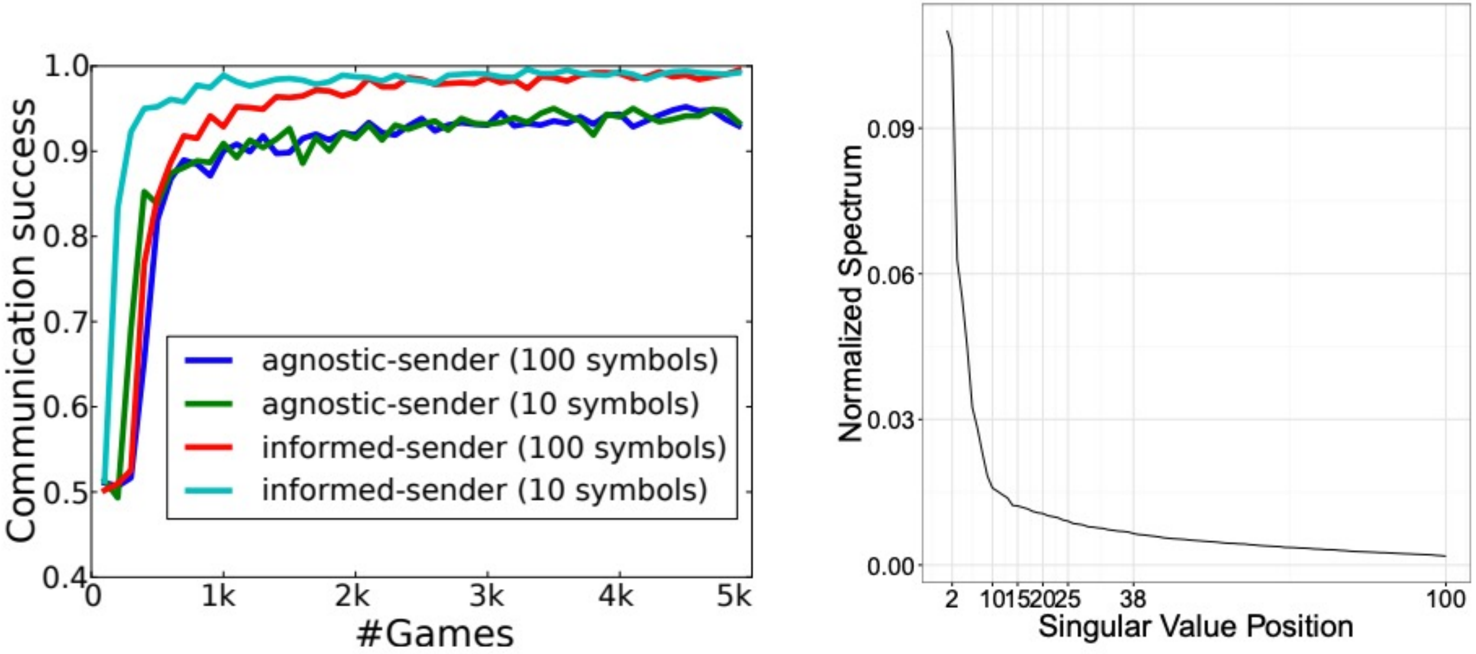


Figure 2: **Left:** Communication success as a function of training iterations, we see that informed senders converge faster than agnostic ones. **Right:** Spectrum of an example symbol usage matrix: the first few dimensions do capture only partial variance, suggesting that the usage of more symbols by the informed sender is not just due to synonymy.

Experiment1 – same-image game

id	sender	vis rep	voc size	used symbols	comm success (%)	purity (%)	obs-chance purity (%)
1	informed	sm	100	58	100	46	27
2	informed	fc	100	38	100	41	23
3	informed	sm	10	10	100	35	18
4	informed	fc	10	10	100	32	17
5	agnostic	sm	100	2	99	21	15
6	agnostic	fc	10	2	99	21	15
7	agnostic	sm	10	2	99	20	15
8	agnostic	fc	100	2	99	19	15

Table 1: Playing the referential game: test results after 50K training games. *Used symbols* column reports number of distinct vocabulary symbols that were produced at least once in the test phase. See text for explanation of *comm success* and *purity*. All purity values are highly significant ($p < 0.001$) compared to simulated chance symbol assignment when matching observed symbol usage. The *obs-chance purity* column reports the difference between observed and expected purity under chance.

Experiment2 – different-image game

- Object-level reference
  - in order to encourage the agents to further pursue high-level semantics
  - removing "common knowledge"
    - if the target is dog, the sender is shown a picture of a Chihuahua and the receiver that of a Boston Terrier

id	sender	vis rep	voc size	used symbols	comm success(%)	purity (%)	obs-chance purity (%)
1	informed	fc	100	43	100	45	21
2	informed	fc	10	10	100	37	19
3	agnostic	fc	100	2	92	23	7
4	agnostic	fc	10	3	98	28	12

Table 2: Playing the referential game with image-level targets: test results after 50K training plays. Columns as in Table 1. All purity values significant at $p < 0.001$.

Experiment2 – different-image game

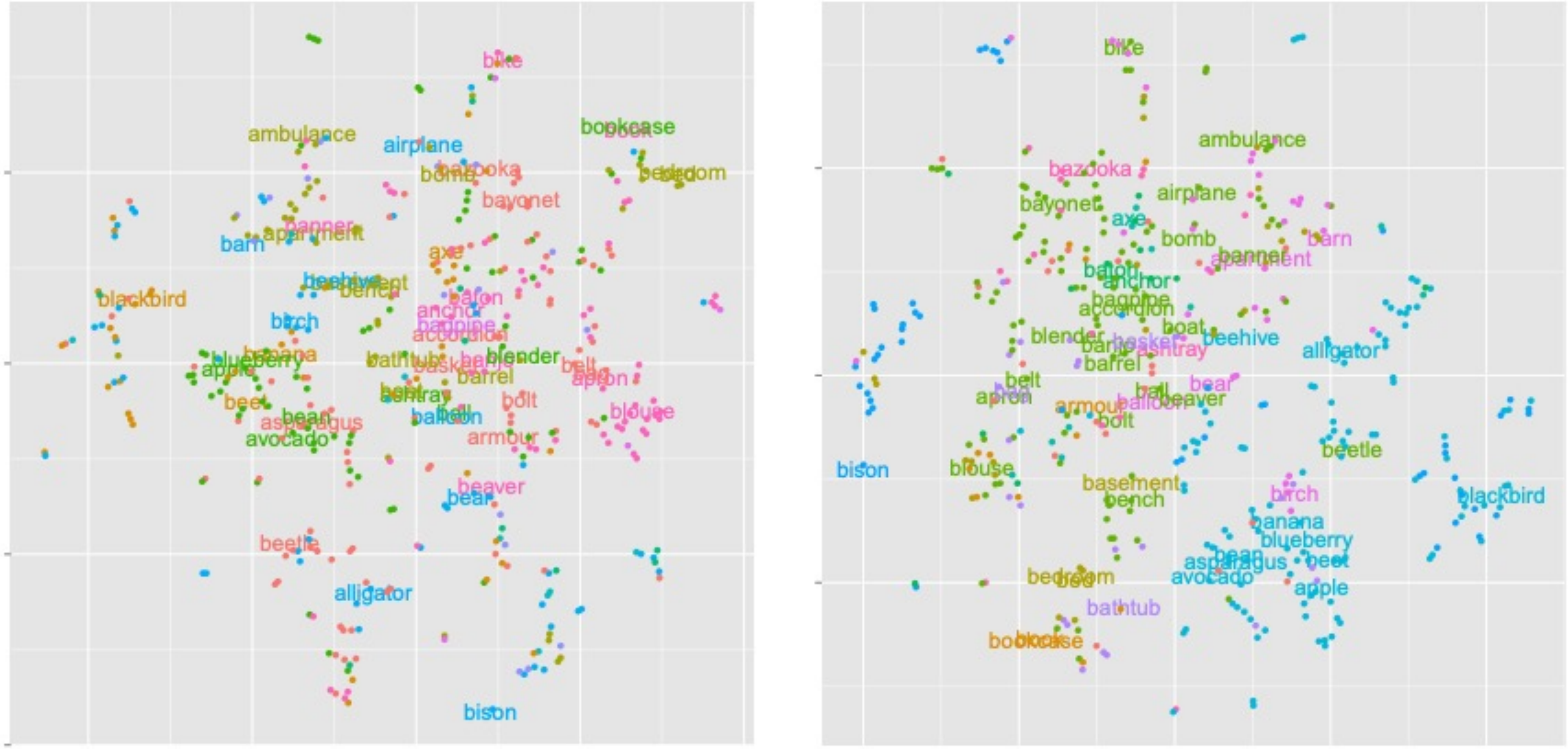


Figure 3: t-SNE plots of object fc vectors color-coded by majority symbols assigned to them by informed sender. Object class names shown for a random subset. **Left:** configuration of 4th row of Table 1. **Right:** 2nd row of Table 2.

Experiment3

- Grounding to human language
  - Referential games + supervised classification
    - 실제 개체명을 이용하여 서로 communicate 하도록
    - no negative effect on communication success
    - uses many more symbols : 88
    - symbol purity increases to 70% (obs-chance purity 37%)

Experiment3

- Grounding to human language
  - 구축된 심볼들이 사람이 해석가능한가?
    - additional data (ReferItGame) : caption에 해당하는 bounding box 제공
      - 각 심볼에 대해, sender가 해당 심볼을 선택하고 reciever가 옳은 선택을 한 이미지들 중 3개를 sampling (총 298개)
      - 298개 쌍 중 8% 만이 ReferItGame의 캡션에 포함됨
        - 대부분의 경우 간접적으로 참조할 수 있는 단어

    - 사람은 어느 정도의 confidence로 학습된 symbol을 그럴듯하다고 생각하는가?
      - 크라우드 소싱
      - 두 개의 이미지와 sender가 선택한 단어가 참가자 에게 주어짐
      - 참가자는 단어와 가장 관련이 있다고 생각되는 그림을 선택, 각 쌍에 대해 10개의 등급을 수집
      - 68% 의 케이스에 경우 옳은 이미지라고 판단
      - “metonymic” 연결을 설정했을 때, 의사소통이 성공하는 경우가 매우 많았음

Figure 4: Example pairs from the ReferItGame set, with word produced by sender. Target images framed in green.

Warp-up

- Referential game이라는 단순한 env를 셋팅
- 새로운 언어 학습 방법론
- 에이전트가 symbol을 만드는, 언어 출현 시뮬레이션

EMERGENCE OF LINGUISTIC COMMUNICATION FROM REFERENTIAL GAMES WITH SYMBOLIC AND PIXEL INPUT Angeliki Lazaridou et al, ICLR 2018

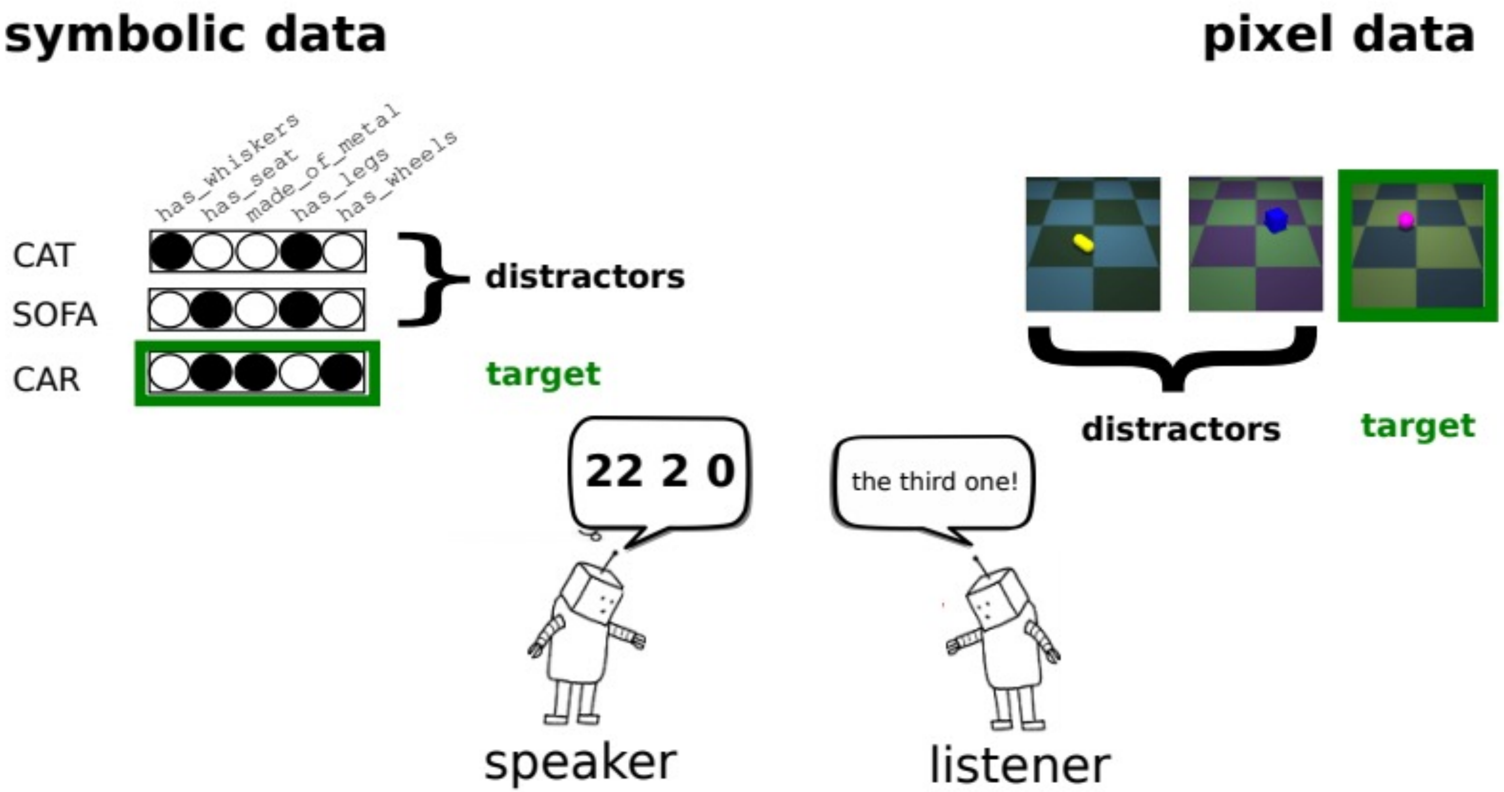


Figure 1: High-level overview of the referential game.

Q&A