# Automatic prediction of aspectual class of verbs in context (ACL 2014)

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# Stative and dynamic meanings of verbs in context

The juice **fills** the glass.
*(stative)*
'something is the case'

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The juice **fills** the glass.
*(stative)*
'something is the case'


She **filled** the glass with juice.
*(dynamic)*
'something happens'

# Ambiguous verb types:
# sometimes both readings are available


The glass was **filled** with juice.
*(both readings)*

# Why predict aspectual class?

- aspectual class of a discourse's finite verbs
  = important factor in conveying / interpreting temporal structure (e.g. Moens & Steedman 1998)
  (other factors: tense, grammatical aspect, mood, completedness)

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- one factor in determing situation entity type (Smith 2003)
  – more on this later

# Aspectual class: linguistic literature

- Vendler (1957): time schemata of English verbs (*lexical aspect*)

| | | |
|---|---|---|
| **states** | *love, own* | STATIVE |
| **activities** | *run, write letters* | DYNAMIC |
| **accomplishments** | *run a mile, write a letter* | |
| **achievements** | *realize, cross the border* | |

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<table>
<tr><td>states</td><td>love, own</td><td>STATIVE</td></tr>
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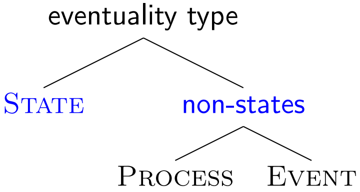
- Bach (1986): sentences




- ...

# Fundamental aspectual class

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= a clause's aspectual class when ignoring any aspectual markers / transformations (following Siegel & McKeown 2000)

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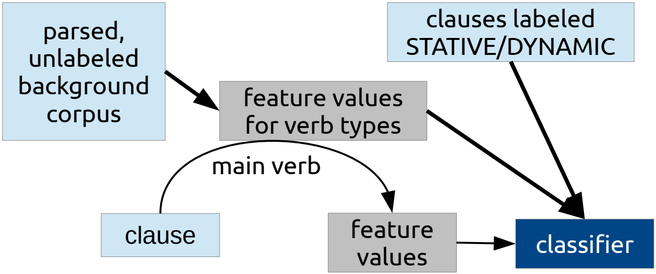
## Example

*John has **kissed** Mary.*

- English perfect → stative (Smith 1991, Katz 2003)
- fundamental aspectual class: *John kiss Mary* → DYNAMIC

# Aspectual class: computational linguistics

## Type-based approaches



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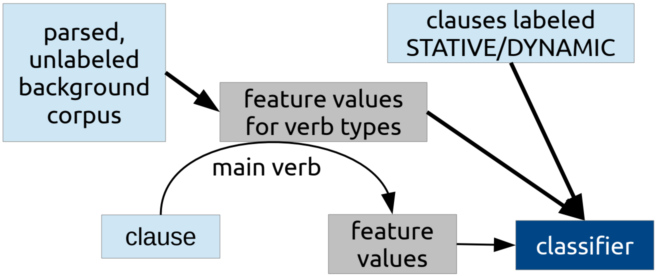


- Klavans & Chodorow (1992): **degrees** of stativity
  $\approx$ tendencies of use are collected for verb types from corpus
  (progressive as indicator)

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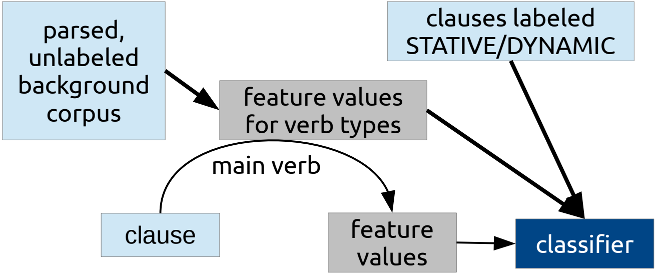
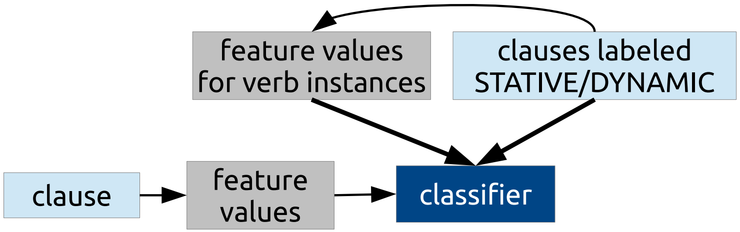



- Klavans & Chodorow (1992): **degrees** of stativity
  $\approx$ tendencies of use are collected for verb types from corpus
  (progressive as indicator)
- Siegel & McKeown (2000): **linguistic indicators**,
  did not beat most-frequent-class baseline $\rightarrow$ main inspiration

# Aspectual class: computational linguistics

**Instance-based approaches**

- Siegel (1998): using direct object of *have*
- TempEval challenges: **event extraction & classification**
  wide range of corpus-based and syntactic-semantic features (e.g. Jung & Stent (2013), Bethard (2013), Chambers (2013))
  Costa & Branco (2013): aspectual features, Portuguese



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Automatic prediction of aspectual class of verbs in context

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**This work:**

Automatic prediction of aspectual class of verbs in context

1. creation & analysis of corpora for this task
2. are type-based features sufficient? (no)
3. do type-based features generalize over verb types? (yes)
4. when are instance-based features helpful?
   (for ambiguous verbs)

# Asp-MASC

- 7875 clauses from the Manually Annotated SubCorpus (MASC) of OANC (Ide et al. 2010): *jokes, letters, news*
  annotated for aspectual class (main verb)

## Example

| | |
|---|---|
| He **assured** her | DYNAMIC |
| that it **was** nonsense, | STATIVE |
| but that Gailhaguet "**knows** my name very well – | STATIVE |

(NYTnewswire2)

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(NYTnewswire2)

- segmentation into clauses: SPADE discourse parser (Soricut & Marcu 2006) + heuristic post-processing
- main verb automatically extracted from dependency parses (Stanford parser), exclude *have/be/none*: 6161 clauses
- 2 annotators: agreed cases → DYNAMIC, STATIVE, BOTH
  disagreed cases: → BOTH

# Asp-MASC: inter-annotator agreement

*Cohen's observed unweighted $\kappa$*

| | complete | | w/o *have/be/none* | |
|---|---|---|---|---|
| **genre** | **clauses** | $\kappa$ | **clauses** | $\kappa$ |
| jokes | 3462 | 0.85 | 2660 | 0.77 |
| news | 2565 | 0.79 | 2075 | 0.69 |
| letters | 1848 | 0.71 | 1444 | 0.62 |
| all | 7875 | 0.80 | 6161 | 0.70 |

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## Agreement: findings

- substantial agreement
- 'difficulty': jokes $<$ news $<$ letters
  - jokes $\approx$ narratives, letters $\approx$ persuasive/argumentative
    $\Rightarrow$ different rhetorical style, more statives in letters

# Asp-MASC: annotator preferences

w/o *have/be/none*, confusion matrix:

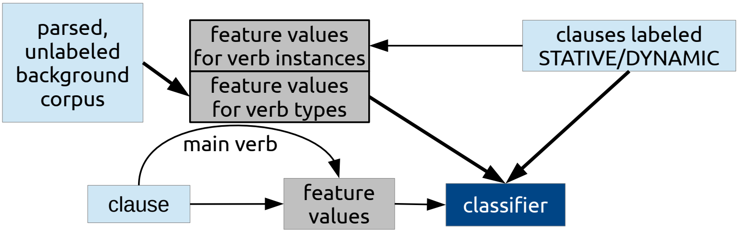
| | | Annotator 2 | | |
|---|---|---|---|---|
| | | DYNAMIC | STATIVE | BOTH |
| Annotator 1 | DYNAMIC | **4464** | 164 | 9 |
| | STATIVE | 434 | **1056** | 29 |
| | BOTH | 5 | 0 | **0** |

## Annotator preferences: findings

- on the disagreed cases, annotator 1 prefers STATIVE, annotator 2 prefers DYNAMIC.
- not uncommon (Beigman Klebanov et al. 2008)

# Method

- three-way classification task: STATIVE/DYNAMIC/BOTH
- (semi-)supervised learning setting:
  Random Forest classifier (Breiman 2001)




- three sets of features:
  1. **linguistic indicator features** (type-based)
  2. **distributional features** (type-based)
  3. **instance-based features**

# Linguistic indicators (LingInd) feature set (type-based)

- idea: **linguistic indicators** (past/present tense, temporal adverb, in-PP, for-PP...) correlate with stative / dynamic readings (Siegel & McKeown 2000)
- count how often instances of a verb type occur with an indicator in a parsed **background corpus**
  $\rightarrow$ we use: Gigaword AFE+XIE, Stanford parser

## Example

verb type: `fill`

feature: `temporal-adverb` feature value: 0.0085

$\Rightarrow$ 0.85% of the occurrences of *fill* in the corpus are modified by one of the temporal adverbs on the list compiled by Siegel (1998).

# Linguistic indicators (LingInd) feature set (type-based)

| Feature | Example |
|---|---|
| frequency | - |
| present | *says* |
| past | *said* |
| future | *will say* |
| perfect | *had won* |
| progressive | *is winning* |
| negated | *not/never* |
| particle | *up/in/...* |
| no subject | - |

Loaiciga et al. (2014)

| Feature | Example (lists) |
|---|---|
| continuous adverb | *continually* *endlessly* |
| evaluation adverb | *better* *horribly* |
| manner adverb | *furiously* *patiently* |
| temporal adverb | *again* *finally* |
| in-PP | *in an hour* |
| for-PP | *for an hour* |

Siegel & McKeown (2000)

# Verb type seed sets

- Lexical Conceptual Structures (LCS) database of English verbs (Dorr 2001)
- Dorr & Olsen (1997): rules to extract 'dynamicity' feature for verb types – we extract three lists of verbs:

## LCS verb type seed sets

1. 188 verbs whose entries in LCS are all stative
   *belong, cost, possess,...*
2. 3760 verbs whose entries in LCS are all dynamic
   *alter, knock, resign,...*
3. 215 verbs that have both stative and dynamic entries in LCS
   *fill, stand, take,...*

# Distributional features (type-based)

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## 3 numeric features per verb type:

1. average cosine similarity with verbs on ‘stative’ LCS seed list
2. average cosine similarity with verbs on ‘dynamic’ LCS seed list
3. average cosine similarity with verbs on ‘mixed’ LCS seed list

# Instance-based features

- extracted from the **clause** to be classified
  (tense/progressive/perfect/voice: see Loaiciga et al. (2014))

| Feature | Values |
|---|---|
| part-of-speech tag of the verb | VB, VBG, VBN, ... |
| tense | present, past, future |
| progressive | true/false |
| perfect | true/false |
| voice | active/passive |
| grammatical dependents | WordNet lexname/POS |

## Example

*A little girl had just* ***finished*** *her first week of school.*

`tense`:*past* `perfect`:*true* `voice`:*active*

`dobj`:*noun.time* `subj`:*noun.person* `particle`:*none*

# Experiments: overview

| feature sets |
|---|
| type-based:<br>- linguistic indicators<br>- distributional features |
| instance-based |

| data |
|---|
| labeled clauses |

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| classification settings |
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| verb types SEEN in training data |
| verb types UNSEEN in training data |
| ONE-LABEL VS. MULTI-LABEL verbs |
| INSTANCE-BASED classification:<br>ambiguous verb types |

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- How effective are the feature sets in each setting?
- Significance testing: McNemar's test with Yates' correction of continuity, $p < 0.01$

# SEEN verbs: labeled training data for verb type available

- Asp-MASC, Random Forest classifier, 10-fold cross validation, distributing instances of verb types over folds
- Lemma = lemma of main verb used as additional feature
- Baseline (Lemma) memorizes most frequent class of verb type in training folds

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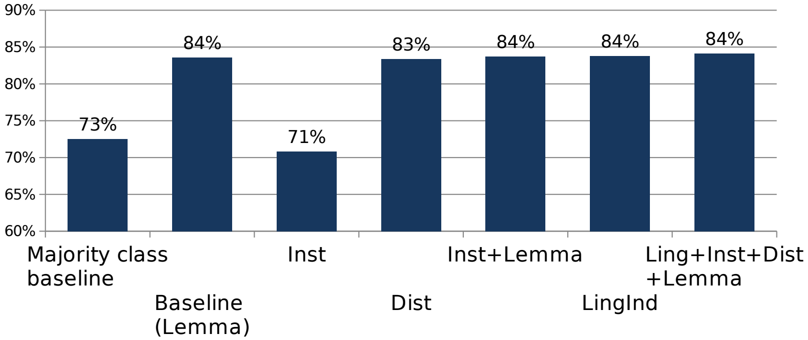
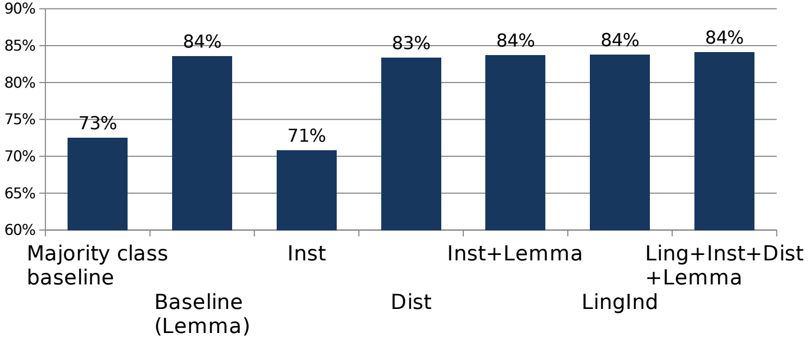


# Seen verbs: labeled training data for verb type available

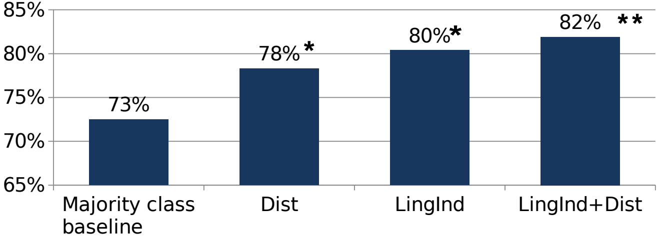
## Seen verb types: findings

All type-based features result in the same performance as using the most frequent class of the type in the training data (no significant improvements).



# UNSEEN verbs: no labeled training data available

- Logistic regression, Asp-MASC, 10-fold cross validation: all occurrences of a verb type in the same fold
- Baseline: most frequent class (DYNAMIC)

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** significantly better than LingInd

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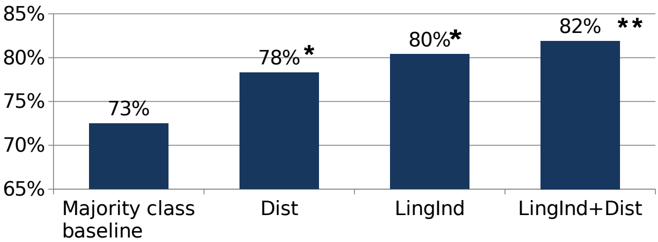


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## UNSEEN verb types: findings

LingInd + Dist features generalize across verb types. Combination works best.

## One-label vs. multi-label verbs

- one-label verbs: all instances in Asp-MASC have the same label (1966 instances, 806 verb types)
- multi-label verbs: instances have differing labels (4195 instances, 264 verb types)
- ‘seen’ setting: Random Forest, 10-fold cross validation

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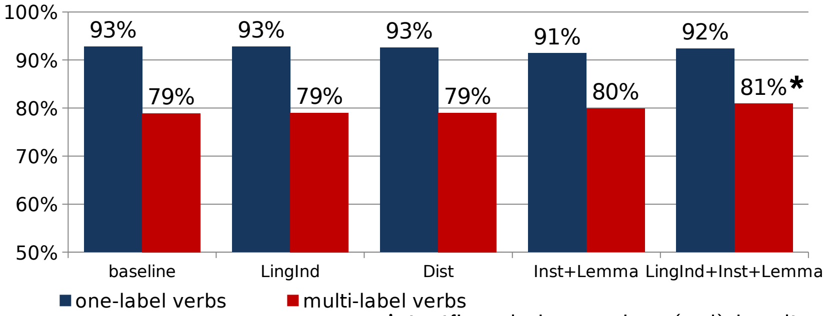
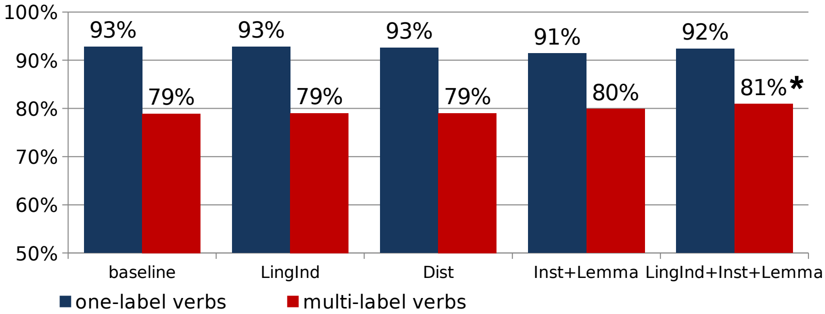



*significantly better than (red) baseline

# One-label vs. multi-label verbs: **Accuracy**

## Multi-label verb types: findings

Type-based features: always select predominant class; but useful bias.
Instance-based features: essential for classifying ambiguous verbs.
⇒ motivation for further investigating ambiguous verbs

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# Instance-based classification: Asp-Ambig data set

- 20 frequent verbs that can occur as either stative or dynamic (selected from LCS list of 'mixed' verb types)
- for each: 138 sentences randomly extracted from Brown corpus
- two annotators mark the aspectual class of the verb in question (highlighted)

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- two annotators mark the aspectual class of the verb in question (highlighted)
- 2667 instances, $\kappa = 0.6$ (Asp-MASC $\kappa = 0.7$)
  1444 DYNAMIC, 697 STATIVE, 526 BOTH

# Instance-based classification

- Asp-Ambig (20 verbs, $\approx$ 138 instances each)
- Random Forest, Leave-One-Out cross validation

| Features | Micro-avg. accuracy |
|---|---|
| majority class baseline | 66.3% |
| type-based features | |
| Inst | 58.1% |
| Inst+Lemma | 71.0% |
| Inst+Lemma+LingInd+Dist | 72.0% |

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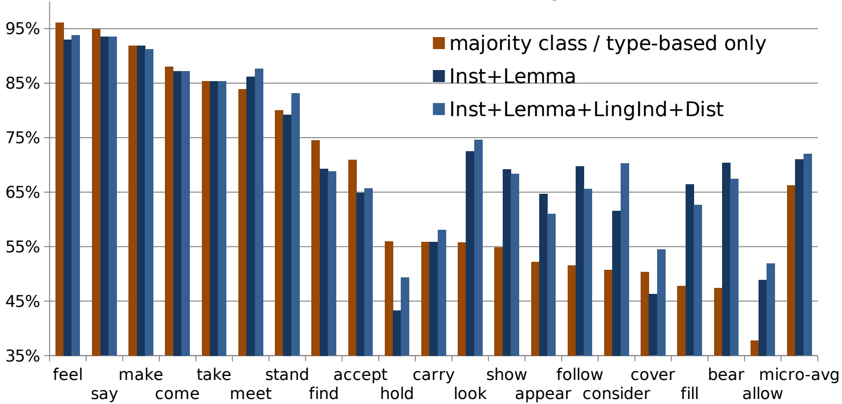
## INSTANCE-BASED classification: findings

Inst features do not generalize across verb types.
Only useful as a feature in combination with the verb type.

# Instance-based classification: **Accuracy**



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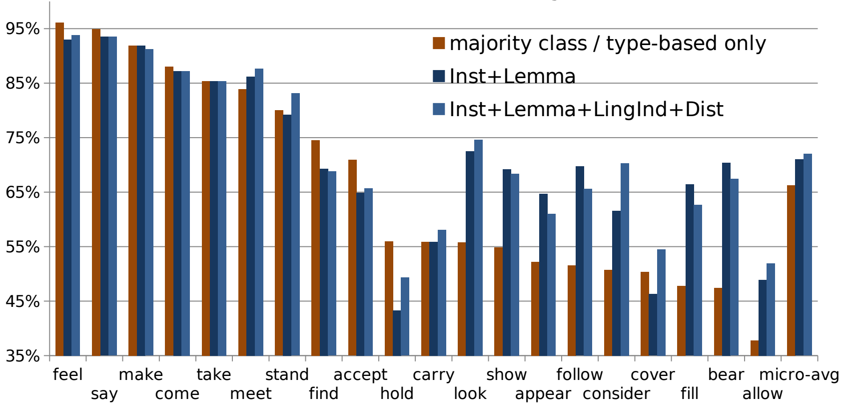


## INSTANCE-BASED classification: findings

The more 'ambiguous' the verb type, the more essential are instance-based features.

Type-based features (bias) helpful? $\rightarrow$ depends on the verb type

# Summary

- **context-aware** approach to automatically predicting aspectual class, new set of distributional features
- two new **corpora**: Asp-MASC & Asp-Ambig

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**Future work**

- a globally well-performing system: multi-stage approach, treating verbs differently according to whether the verb’s aspectual class distribution is highly skewed
- gather more data & apply more features

# Thanks to:

Ambika Kirkland & Ruth Kühn

Omri Abend, Mike Lewis, Annie Louis, Manfred Pinkal,
Mark Steedman, Stefan Thater, Bonnie Webber

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Backup Slides

# SEEN verbs: labeled training data for verb type available

- Asp-MASC, Random Forest classifier, 10-fold cross validation, distributing instances of verb types over folds
- Lemma = lemma of main verb used as additional feature

| Features | Accuracy (%) |
|---|---|
| Majority class baseline (DYNAMIC) | 72.5 |
| Baseline (Lemma) * | 83.6 |
| LingInd | 83.8 |
| Inst | 70.8 |
| Inst+Lemma | 83.7 |
| Dist | 83.4 |
| LingInd+Inst+Dist+Lemma | 84.1 |

*memorizes most frequent class of verb type in training folds

## SEEN verb types: findings

All type-based features result in the same performance as using the most frequent class of the type in the training data (no significant

# Instance-based classification

- Asp-Ambig, Random Forest, Leave-One-Out cross validation
- using Inst features alone: acc. 58.1%

| Verb | # of inst. | Majority Class | | Inst +Lemma | Inst +Lemma +LingInd +Dist |
|---|---|---|---|---|---|
| *feel* | 128 | **96.1** | stat | 93.0 | 93.8 |
| *say* | 138 | **94.9** | dyn | 93.5 | 93.5 |
| *make* | 136 | **91.9** | dyn | 91.9 | 91.2 |
| *come* | 133 | **88.0** | dyn | 87.2 | 87.2 |
| *take* | 137 | **85.4** | dyn | 85.4 | 85.4 |
| *meet* | 130 | 83.9 | dyn | 86.2 | **87.7** |
| *stand* | 130 | 80.0 | stat | 79.2 | **83.1** |
| *find* | 137 | **74.5** | dyn | 69.3 | 68.8 |
| *accept* | 134 | **70.9** | dyn | 64.9 | 65.7 |
| *hold* | 134 | **56.0** | both | 43.3 | 49.3 |
| *carry* | 136 | 55.9 | dyn | 55.9 | **58.1** |
| *look* | 138 | 55.8 | dyn | 72.5 | **74.6** |
| *show* | 133 | 54.9 | dyn | **69.2** | 68.4 |
| *appear* | 136 | 52.2 | stat | **64.7** | 61.0 |
| *follow* | 122 | 51.6 | both | **69.7** | 65.6 |
| *consider* | 138 | 50.7 | dyn | 61.6 | **70.3** |
| *cover* | 123 | 50.4 | stat | 46.3 | **54.5** |
| *fill* | 134 | 47.8 | dyn | **66.4** | 62.7 |
| *bear* | 135 | 47.4 | dyn | **70.4** | 67.4 |
| *allow* | 135 | 37.8 | dyn | 48.9 | **51.9** |
| micro-avg. | 2667 | 66.3 | | **71.0*** | **72.0*** |

# Asp-Ambig: confusion matrix

| | | Annotator 2 | | |
|---|---|---|---|---|
| | | DYNAMIC | STATIVE | BOTH |
| Annotator 1 | DYNAMIC | **1444** | 201 | 54 |
| | STATIVE | 168 | **697** | 20 |
| | BOTH | 44 | 31 | **8** |

# UNSEEN verbs: no labeled training data available

- Logistic regression, Asp-MASC, 10-fold cross validation: all occurrences of a verb type in the same fold
- Baseline: most frequent class (DYNAMIC)

| | Features | Accuracy (%) |
|---|---|---|
| 1 | Baseline | 72.5 |
| 2 | Dist | 78.3* |
| 3 | LingInd | 80.4* |
| 4 | LingInd+Dist | **81.9*†** |

## UNSEEN verb types: findings

LingInd + Dist features generalize across verb types.
Combination works best.

# ONE-LABEL vs. MULTI-LABEL verbs

| Data | Features | Acc. (%) |
|---|---|---|
| one-label verbs (1966 inst.) | Baseline | 92.8 |
| | LingInd | 92.8 |
| | Dist | 92.6 |
| | Inst+Lemma | 91.4* |
| | LingInd+Inst+Lemma | 92.4 |
| multi-label verbs (4195 inst.) | Baseline | 78.9 |
| | LingInd | 79.0 |
| | Dist | 79.0 |
| | Inst | 67.4* |
| | Inst+Lemma | 79.9 |
| | LingInd+Inst+Lemma | **80.9*** |
| | LingInd+Inst+Lemma+Dist | 80.2* |

## MULTI-LABEL verb types: findings

Type-based features always select predominant class.

# ONE-LABEL vs. MULTI-LABEL verbs

| Class | Acc.(%) | P | R | F |
|---|---|---|---|---|
| Baseline (Lemma) | | | | |
| micro-avg. | 78.9 | 0.75 | 0.79 | 0.76 |
| LingInd+Inst+Lemma | | | | |
| DYNAMIC | | 0.84 | 0.95 | 0.89 |
| STATIVE | | 0.76 | 0.69 | 0.72 |
| BOTH | | 0.51 | 0.24 | 0.33 |
| micro-avg. | 80.9* | 0.78 | 0.81 | 0.79 |

Table: **Experiment 3**: 'multi-label', precision, recall and F-measure, detailed class statistics for the best-performing system from Table

## MULTI-LABEL verb types: findings

Significant gains of 2% in accuracy and 3% in F-measure (absolute). 'Difficulty': DYNAMIC< STATIVE< BOTH