Three-order normalized PMI and other lessons in tensor analysis of verbal selectional preferences

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>2 order association

- *factor affect ability*
- collocation extraction (Bouma, 2009)
    - idiosyncrasy in the linguistic distribution
        - reduced syntactic modifiability
    - reduced semantic compositionality
        - a sense of the combination is habitual or even fixed

Overview

Association scores

- Linguistic frequencies form *sparse* arrays
- frequencies span many orders of magnitude, *Zipf* = power law
  - Manin (2008) and Gittens, Achlioptas, and Mahoney (2017)
- for scale, sparse tensors populated with sophisticated scores
- $\log(f + 1)$
  - (Pennington, Socher, and Manning, 2014; Sharan and Valiant, 2017)
- three-mode PPMI

$$\log \frac{p(x, y, z)}{p(x)p(y)p(z)}$$

- Positivity $\Leftarrow$ sparse
  - attribute higher scores to actual co-occurrences than unattested
  - replaces negative PMI entries with zero
- two different three-variable generalization of PPMI
- We generalize Log Dice (Rychlý, 2008) to three axes

$$\log \frac{3f(x, y, z)}{f(x) + f(y) + f(z)} + c$$

Higher-order PMI Cruys (2011)

- point-wise measure: $\mathbb{E}(PMI) = MI$
- two multivariate generalizations of mutual information (Shannon and Weaver, 1949) $\Rightarrow$ two multivariate point-wise variants
- *Interaction information* (McGill, 1954) and
  - based on the notion of conditional mutual information
    - inclusion and exclusion principle (szitaformula),
      except it has the numerator and the denominator swapped to ensure a proper set-theoretic measure

$$\log \frac{p(x,y)p(x,z)p(y,z)}{p(x,y,z)p(x)p(y)p(z)}$$

- *Total correlation* (Watanabe, 1960)
  - quantifies the amount of information that is shared among the variables

$$\log \frac{p(x,y,z)}{p(x)p(y)p(z)}$$

  - we just call it PMI
    - Following the literature (Villada Moirón, 2005; Cruys, 2009; Cruys, Poibeau, and Korhonen, 2013; Bailey, Meyer, and Aeron, 2018)

Salience and normalization

$$\log \frac{p(xy)}{p(x)p(y)}$$

- biased towards rare events
  - Turney and Pantel (2010), Levy et al. (2015), and Zhuang et al. (2018)
- salience (Sketch Engine, Kilgarriff et al. (2004))
  - $*$=log f
- normalized variants (Bouma, 2009)
  - several ways of normalizing PMI, as
    the maximum value coincides with several other measures
  - $-\log p(x, y)$
  - $H(X, Y)$
  - we divide by $-\log(p(x, y, z))$

Overview

1. Association scores
2. Low-rank decompositions and tensors
3. Experiments: similarity of English subject-verb-object triples

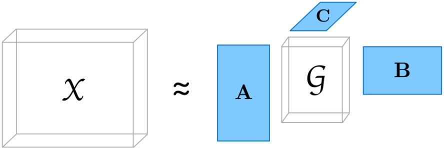
Low-rank decompositions and tensors

- Turney and Pantel (2010): "four ways of looking at SVD" (i.e. LSA)
  - latent meaning
  - noise reduction
  - indirect aka. high-order co-occurrence
    - when two words appear in similar contexts
  - sparsity reduction
- two axes:
  - words and documents (LSA, Landauer and Dumais (1997))
  - words and dependency contexts (Levy and Goldberg, 2014a)
  - target and context words (standard words embeddings, Levy and Goldberg (2014b) and Pennington, Socher, and Manning (2014))
- tensor: ndim array, *mode* (data fusion), *axis*
- product, decomposition
- generalizations of low-rank matrix decomposition

Tucker decomposition aka. Higher Order SVD

Tucker (1966)

- no single generalization of the SVD concept
- factorizes a tensor into
  - a core tensor G
  - multiplied by a matrix along each mode
- can be computed efficiently



- In the case of

$$\text{subject} \times \text{verb} \times \text{object}$$

  - rows of the three matrices contain embedding vectors of subjects, verbs, and objects (so far, the CDP and Tucker are thee same)
  - entries of G determine the levels of interactions between s, v, o

non-negative decomposition

- Tucker decomposition is not unique
  - we can transform G without affecting the fit if we apply the inverse of that transformation to the factor matrices
- Uniqueness can be improved (Kolda and Bader, 2009) by imposing e.g. sparsity, making the elements small, or making the core "all-orthogonal", non-negativity (Zhou et al., 2015) and independence (Lahat, Adali, and Jutten, 2015)

Canonical Polyadic Decomposition (CPD)

Carroll and Chang (1970)

- CPD aka. CanDecomp, Parallel Factor model, rank decomp, Kruskal
- for latent parameter estimation

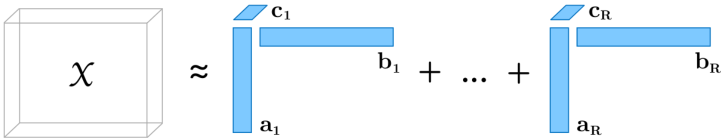


Figure: CDP expresses a tensor as a linear combination of rank-1 tensors. Figure from Rabanser, Shchur, and Günnemann (2017)

- alternating least squares, ALS
  (Carroll and Chang, 1970; Harshman, 1970)
- convergence: no guarantee, and cannot be detected in a trivial way
- Orth-ALS Sharan and Valiant (2017) improves on ALS
- non-negative

Overview

1. Association scores
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Corpus and implementational details

- task (Kartsaklis and Sadrzadeh, 2014)
- occurrence counts of $\langle$subject, verb, object$\rangle$ triples
- in Universal Dependencies (Nivre et al., 2016) terms, `nsubj`, `ROOT`, and `dobj`, with the `upos` of the `ROOT` starting with `VB`)
- from the automatically dependency-parsed corpus DepCC (Panchenko et al., 2018),
- irrespectively of whether there were other arguments or adjuncts
- Empty fillers
- tensorly (Kossaifi et al., 2016)
- `https://github.com/makrai/verb-tensor`

Hyper-parameters

- rank, inclusion of empty fillers, and frequency cutoff
- tuning: Tucker $\xrightarrow{?}$ CPD
- trade-off related to the size of the decomposition

Best hyper-parameters

assoc measure	unfilled	cutoff	non-negative	decomp algo	rank	corr
pmi-sali	included	1 000 000	non-neg	parafac	64	0.7359
pmi-sali	included	1 000 000	non-neg	parafac	128	0.7097
pmi	included	1 000 000	non-neg	parafac	64	0.6857
pmi-sali	included	1 000 000	non-neg	parafac	32	0.6773
pmi-sali	included	*300 000*	non-neg	parafac	64	0.6630
npmi	included	1 000 000	non-neg	parafac	64	0.6602
dice-sali	included	1 000 000	non-neg	parafac	64	0.4709
pmi-sali	excluded	1 000 000	non-neg	parafac	64	0.4578
pmi-sali	included	1 000 000	*general*	parafac	64	0.4560
ldice	included	1 000 000	non-neg	parafac	64	0.4409
log-freq	included	1 000 000	non-neg	parafac	64	0.4322
iact-sali	included	1 000 000	non-neg	parafac	64	0.4112
niact	included	1 000 000	non-neg	parafac	64	0.4068
pmi-sali	included	*3 000 000*	non-neg	parafac	64	0.3936
iact	included	1 000 000	non-neg	parafac	64	0.3248
pmi-sali	included	1 000 000	non-neg	*tucker*	64	0.2989

Latent dimensions in non-negative ParaFac decomposition

dim	words
0	∅, that, which, it, *story*, he, they, who, what, one, she, work, event, -rrb-, this, you...
0	catch, attract, draw, pay, deserve, capture, gain, grab, get, receive, focus, require,...
0	attention, eye, crowd, interest, fire, visitor, audience, conclusion, breath, people, ...
1	∅, who, we, he, I, you, she, they, -rrb-, *student*, member, people, group, Center, parti...
1	attend, host, hold, organize, schedule, enjoy, join, arrange, cancel, miss, watch, pla...
1	meeting, event, conference, session, party, show, school, class, dinner, church, tour,...
2	that, which, it, this, ∅, *change*, factor, they, choice, condition, decision, issue, -rr...
2	affect, impact, influence, improve, hurt, reflect, benefit, change, damage, enhance, a...
2	ability, performance, health, outcome, life, quality, result, business, development, e...
3	file, which, page, site, that, it, book, report, section, document, collection, websit...
3	contain, include, provide, have, list, feature, display, show, comprise, present, give...
3	information, link, material, number, list, datum, name, content, statement, reference,...

Table: Latent dimensions with Non-negative ParaFac

Comparing subject and object vectors

- how differently nouns behave as subjects and as objects
- complementary to symmetric factorization
  - symmetry constraints between the embeddings of the same entities in different modes (Bailey, Meyer, and Aeron, 2018)
  - now: between the embeddings of the same noun as a subject vs object
- CPD maps nouns as subjects and objects in the same space
- (non-negative) CPD decomposition
  - with the hyper-parameters that proved best in English SVO-similarity
- (unnormalized) dot product similarity
  - between the subject and object vector of each noun
  - nouns sorted by this similarity
- largest distance: $\emptyset$, *he, she, they, I, device, system, that, you, it...*
- most symmetric: *doubt, reality, future, same, hope, feeling, mine*
- possible explanation
  - personal pronouns: frequent as agent, rare as patient
  - *doubt* can be framed in language both as animate and as inanimate
    - not alive in the biological sense, but often attributed agentive role in "metaphorical use"

“Follow-up” and future

- clustering
- Hungarian and preverbs
- benefits of tensor decomposition
  - comparison: only matrices (and matrix decomposition techniques)
  - the tensors were aggregated along their different modes
- standard word embeddings (different roles conflate)
- comparison to contextualized models (e.g. BERT) would be
  - averaging contextual representations of words when being present in a specific role
- In English, nouns can act as verbs as well
  - comparing the vector of man as a verb and as a subject
- leaving out function words such as pronouns
  - the qualitative evaluation shows that they are just noise
- "what have we shown and where to go from here" (reviewer 2)
  - linguistic dimensions of the research (latent dimension, difference between each noun as a subject versus an object)

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Bibliography I

Bailey, Eric, Charles Meyer, and Shuchin Aeron (2018). "Learning semantic word respresentations via tensor factorization". arXiv:1704.02686. URL: https://openreview.net/forum?id=B1kIr-WRb (cit. on pp. 5, 17).

Bouma, Gerlof (2009). "Normalized (pointwise) mutual information in collocation extraction". In: *GSCL 2009: International Conference of the German Society for Computational Linguistics and Language Technology* (cit. on pp. 2, 6).

Carroll, J. D. and J. J. Chang (1970). "Analysis of individual differences in multidimensional scaling via an N-way generalization of "Eckart-Young" decomposition". In: *Psychometrika* 35, pp. 283–319 (cit. on p. 11).

Church, Kenneth W. and Patrick Hanks (1990). "Word association norms, mutual information, and lexicography". In: *Computational Linguistics* 16.1, pp. 22–29.

Cruys, Tim Van de (Mar. 2009). "A Non-negative Tensor Factorization Model for Selectional Preference Induction". In: *Proceedings of the Workshop on Geometrical Models of Natural Language Semantics*. Athens, Greece: Association for Computational Linguistics, pp. 83–90. URL: https://www.aclweb.org/anthology/W09-0211 (cit. on p. 5).

Bibliography II

Cruys, Tim Van de (June 2011). "Two Multivariate Generalizations of Pointwise Mutual Information". In: *Proceedings of the Workshop on Distributional Semantics and Compositionality*. Portland, Oregon, USA: Association for Computational Linguistics, pp. 16–20. URL: https://www.aclweb.org/anthology/W11-1303 (cit. on p. 5).

Cruys, Tim Van de, Thierry Poibeau, and Anna Korhonen (June 2013). "A Tensor-based Factorization Model of Semantic Compositionality". In: *Proceedings of the 2013 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*. Atlanta, Georgia: Association for Computational Linguistics, pp. 1142–1151. URL: https://www.aclweb.org/anthology/N13-1134 (cit. on p. 5).

Gittens, Alex, Dimitris Achlioptas, and Michael W. Mahoney (2017). "Skip-Gram – Zipf + Uniform = Vector Additivity". In: *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. Vancouver, Canada: Association for Computational Linguistics, pp. 69–76. DOI: 10.18653/v1/P17-1007. URL: http://aclweb.org/anthology/P17-1007 (cit. on p. 4).

Bibliography III

Harshman, R. A. (1970). “Foundations of the PARAFAC procedure: Models and conditions for an “explanatory” multi-modal factor analysis”. In: *UCLA Working Papers in Phonetics* 16, pp. 1–84. URL: http://publish.uwo.ca/~harshman/wpppfac0.pdf (cit. on p. 11).

Kalivoda, Ágnes (Jan. 2019). “Véges erőforrás végtelen sok igekötős igére [A finite resource for infinitely many Hungarian particle verbs]”. In: *XV. Magyar Számítógépes Nyelvészeti Konferencia*. Ed. by Gábor Berend, Gábor Gosztolya, and Veronika Vincze, pp. 331–344 (cit. on p. 32).

Kartsaklis, Dimitri and Mehrnoosh Sadrzadeh (June 2014). “A Study of Entanglement in a Categorical Framework of Natural Language”. In: *The 11th workshop on Quantum Physics and Logic*. arXiv:1412.8102 (cit. on p. 13).

Kilgarriff, Adam et al. (July 2004). “Sketch engine”. In: *Proceedings of Euralex*. Ed. by Geoffrey Williams and Sandra Vessier. Lorient, Université de Bretagne-Sud, Faculté des lettres et des sciences humaines, pp. 105–116 (cit. on p. 6).

Kolda, Tamara G and Brett W Bader (2009). “Tensor decompositions and applications”. In: *SIAM review* 51.3, pp. 455–500 (cit. on p. 10).

Bibliography IV

Kossaifi, Jean et al. (2016). "Tensorly: Tensor learning in python". In: *Journal of Machine Learning Research (JMLR)* 20. arXiv preprint arXiv:1610.09555, pp. 1–6 (cit. on p. 13).

Lahat, Dana, Tülay Adali, and Christian Jutten (2015). "Multimodal data fusion: an overview of methods, challenges, and prospects". In: *Proceedings of the IEEE* 103.9, pp. 1449–1477 (cit. on p. 10).

Landauer, Thomas K and Susan T Dumais (1997). "A solution to Plato's problem: The latent semantic analysis theory of acquisition, induction, and representation of knowledge.". In: *Psychological review* 104.2, p. 211 (cit. on p. 8).

Levin, Beth (1993). *English Verb Classes and Alternations: A Preliminary Investigation*. University of Chicago Press (cit. on p. 29).

Levy, Omer and Yoav Goldberg (June 2014a). "Dependency-Based Word Embeddings". In: *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*. Baltimore, Maryland: Association for Computational Linguistics, pp. 302–308. URL: `http://www.aclweb.org/anthology/P14-2050` (cit. on p. 8).

Bibliography V

Levy, Omer and Yoav Goldberg (2014b). "Neural Word Embedding as Implicit Matrix Factorization". In: *Advances in Neural Information Processing Systems 27*. Ed. by Z. Ghahramani et al., pp. 2177–2185 (cit. on p. 8).

Levy, Omer et al. (2015). "Do Supervised Distributional Methods Really Learn Lexical Inference Relations?" In: *Proceedings of the 2015 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*. Denver, Colorado: Association for Computational Linguistics, pp. 970–976. DOI: 10.3115/v1/N15-1098. URL: https://www.aclweb.org/anthology/N15-1098 (cit. on p. 6).

Manin, Dmitrii Y. (2008). "Zipf's Law and Avoidance of Excessive Synonymy". In: *Cognitive Science* 32 (7), pp. 1075–1098 (cit. on p. 4).

McGill, William (1954). "Multivariate information transmission". In: *Transactions of the IRE Professional Group on Information Theory* 4.4, pp. 93–111 (cit. on p. 5).

McInnes, Leland, John Healy, and Steve Astels (Mar. 2017). "hdbscan: Hierarchical density based clustering". In: *The Journal of Open Source Software* 2.11. DOI: 10.21105/joss.00205. URL: https://doi.org/10.21105%2Fjoss.00205 (cit. on p. 32).

Bibliography VI

McInnes, Leland et al. (2018). "UMAP: Uniform Manifold Approximation and Projection". In: *The Journal of Open Source Software* 3.29, p. 861 (cit. on p. 32).

Nivre, Joakim et al. (May 2016). "Universal Dependencies v1: A Multilingual Treebank Collection". In: *Proc. LREC 2016*, pp. 1659–1666 (cit. on p. 13).

Panchenko, A et al. (2018). "Building a Web-Scale Dependency-Parsed Corpus from Common Crawl". In: *Proceedings of LREC 2018*. ELRA (cit. on p. 13).

Pennington, Jeffrey, Richard Socher, and Christopher Manning (2014). "Glove: Global Vectors for Word Representation". In: *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. Doha, Qatar: Association for Computational Linguistics, pp. 1532–1543. DOI: 10.3115/v1/D14-1162. URL: http://www.aclweb.org/anthology/D14-1162 (cit. on pp. 4, 8).

Rabanser, Stephan, Oleksandr Shchur, and Stephan Günnemann (Nov. 2017). "Introduction to Tensor Decompositions and their Applications in Machine Learning". arXiv:1711.10781 [stat.ML]. URL: http://arxiv.org/abs/1711.10781v1 (cit. on p. 11).

Rychlý, Pavel (2008). "A Lexicographer-Friendly Association Score". In: *Proceedings of Recent Advances in Slavonic Natural Language Processing*, pp. 6–9 (cit. on p. 4).

Bibliography VII

Sass, Bálint (2015). "28 millió szintaktikailag elemzett mondat és 500000 igei szerkezet [28 million syntactically analyzed sentences and 500 000 verb constructions in Hungarian]". In: *XI. Magyar Számítógépes Nyelvészeti Konferencia (MSZNY 2015)*. Ed. by Tanács Attila, Varga Viktor, and Vincze Veronika. Szegedi Tudományegyetem Informatikai Tanszékcsoport, pp. 303–308. ISBN: 978-963-306-359-0 (cit. on p. 32).

Shannon, Claude E. and Warren W. Weaver (1949). *The Mathematical Theory of Communication*. Urbana: University of Illinois Press (cit. on p. 5).

Sharan, Vatsal and Gregory Valiant (Aug. 2017). "Orthogonalized ALS: A Theoretically Principled Tensor Decomposition Algorithm for Practical Use". In: *Proceedings of the 34th International Conference on Machine Learning, ICML 2017*, pp. 3095–3104. URL: `http://proceedings.mlr.press/v70/sharan17a.html` (cit. on pp. 4, 11).

Szécsényi, Tibor (Jan. 2019). "Argumentumszerkezet-variánsok korpusz alapú meghatározása [Corpus-based identification of Hungarian argument structure variants]". In: *XV. Magyar Számítógépes Nyelvészeti Konferencia*. Ed. by Gábor Berend, Gábor Gosztolya, and Veronika Vincze. Szegedi Tudományegyetem TTIK, Informatikai Intézet, pp. 315–331 (cit. on p. 32).

Tucker, Ledyard R (1966). "Some mathematical notes on three-mode factor analysis". In: *Psychometrika* 31.3, pp. 279–311 (cit. on p. 9).

Bibliography VIII

Turney, Peter D. and Patrick Pantel (2010). "From Frequency to Meaning: Vector Space Models of Semantics". In: *Journal of Artificial Intelligence Research* 37, pp. 141–188 (cit. on pp. 6, 8).

Villada Moirón, M. B. (2005). "Data-driven identification of fixed expressions and their modifiability". PhD thesis. University of Groningen (cit. on p. 5).

Watanabe, Satosi (1960). "Information theoretical analysis of multivariate correlation". In: *IBM Journal of research and development* 4.1, pp. 66–82 (cit. on p. 5).

Zhou, Guoxu et al. (2015). "Efficient nonnegative tucker decompositions: Algorithms and uniqueness". In: *IEEE Transactions on Image Processing* 24.12, pp. 4990–5003 (cit. on p. 10).

Zhuang, Yimeng et al. (2018). "Quantifying Context Overlap for Training Word Embeddings". In: *EMNLP* (cit. on p. 6).

Outline

- Az igevektorok klaszterezése
- Future and past work: Hungarian

- Levin (1993)
- verb clustering:
  - *mond állít elmond javasol nan ír szeret közöl válaszol*
  - *encourage, invite, know, welcome, see, advise, send*
- `UMAP(n_components=32, metric='cosine')`
- `HDBSCAN(min_cluster_size=10, min_samples=5)`
- tapasztalat: KPI Környezeti Adaptáció, Antarktiszi áttelelő csoportok naplóiban mondatklaszterezés

cluster	verbs
-1	be, go, take, come, give, look, work, provide, help, show, inclu...
45	meet, understand, drive, carry, perform, complete, finish, ident...
5	kill, catch, shoot, feed, email, marry, wake, date, judge, bless...
20	care, listen, gon, complain, pray, dream, wan, subscribe, swear,...
27	break, push, lay, stick, roll, touch, press, suck, kick, shake, ...
1	commit, expose, separate, heal, distinguish, kid, free, devote, ...
4	run, leave, open, enter, visit, fill, close, reserve, clean, cro...
6	tell, ask, call, thank, please, join, contact, draw, become, ass...
42	add, eat, prepare, drink, spread, cook, burn, taste, smell, pour...
29	check, view, click, display, generate, update, access, search, s...
3	do, make, think, know, see, want, find, feel, love, like, hear, ...
7	remind, strike, worry, blow, inspire, bother, surprise, confuse,...
11	improve, cover, protect, represent, maintain, achieve, ensure, a...
19	live, laugh, sing, cry, smile, relax, lean, dance, breathe, star...
12	have, get, need, receive, win, lose, seek, assume, earn, gain, o...
18	start, happen, begin, continue, lead, end, occur, prove, result,...

Outline

- Az igevektorok klaszterezése
- Future and past work: Hungarian

Preverbs

- prevlex (Kalivoda, 2019)
- preverbs (igekötők) interfere with argument structure and ambiguity

preverb	verb	args					gloss
∅	bíz(ik)	NOM		-bAn 'in'			trust sth
(rá) 'onto'	bíz	NOM	ACC		-rA 'onto'		entrust sg to sy
meg Perfect	bíz(ik)	NOM		-bAn 'in'			trust sy
meg Perfect	bíz	NOM	ACC			INS	entrust sy with sg
el 'away'	bíz(za)	NOM	self-ACC				get conceited

Table: Argument structure variants of the Hungarian verb *bíz(ik)* based on Szécsényi (2019).

- verb constructions from the Mazsola DB (Sass, 2015)
- *subject* (× *preverb*) × *verb* × *object* tensor
- UMAP to 10 dim (McInnes et al., 2018),
- clustering with HDBScan (McInnes, Healy, and Astels, 2017)
  - following the recommendations at readthedocs

The smallest clusters, preverbs separated

- vigyáz mosolyog csodálkozik bólint legyint bólogat
- kiált bámul szül les ordít könyörög
- halad mozog fejlődik erősöd versenyez küszködik
- jelent elérik követel tervez kíván tapasztal termel
- fekszik csap zárul telepedik fékez ereszkedik játszódik
- csatlakozik tiltakozik érdeklődik viselkedik reménykedik csalódik kételkedik
- létez létezik bizonyul érvényesül vál különbözik megerősöd
- érkezik találkozik utazik utaz távozik távoz tartózkodik játsz
- születik szerepel utal örül lakik emlékszik emlékezik haragszik gratulál
- nő csökken változik emelkedik növekedik növekszik bővül mérséklődik drágul
- rendelkezik vonatkozik gondoskodik irányul alapul minősül intézkedik módosul
- kerül lép számol következik mutatkozik kapcsolódik fejeződik avatkozik
- kinull elnull meglesz benull mar visszanull felnull lenull idenull kilesz odanull

The smallest clusters, preverbs not separated

- kínál szállít előállít behoz bevet
- szán szab kitölt meghosszabbít igazít
- megfelel számol kitér eltér törekedik kiindul
- megjelenik keletkezik hat hangzik terjed szaporodik
- születik létez létezik elkészül megszületik módosul
- oszt süt old fúj kiválik gyújt
- elfog eltávolít aláz elbocsát kivégez kihallgat
- benyújt kidolgoz terjeszt bead elvet előterjeszt beterjeszt
- menekül hozzájut megismerkedik bukkan bekapcsolódik elválik megválik
- megvásárol értékesít eljuttat beszerez megtekint továbbít lefoglal tárol
- tesz elfogad támogat használ megtesz elutasít visszautasít nehezít
- folytat kezd befejez lezár megnyit elhalaszt lebonyolít lefolytat
- magyaráz ismertet közzétesz megismétel összefoglal kommentál összegez tár
- mesél cserél megbocsát üzen szokik felhoz mer megiszik örököl kavar