Appendix A
Code List

Codes are pushed to github for public access.

- A python program is implemented for the experiment described in Chap. 4, and located at

  https://github.com/gnodisnait/bp94nball

- A python package is implemented for structural imposition onto word-embeddings described in Chap. 6. The source code, along with evaluation scripts, are located at

  https://github.com/gnodisnait/nball4tree

- As part of the P3ML project,[1] the nball4tree package is used to construct $\mathcal{N}$-Ball embeddings in Arabic, Albanian, Chinese, Hindi, German, Russian during the IPEC Lab "AI Language Technology". Codes are located at

  https://github.com/p3ml/ai_language_technology

- A python package is developed for Triple Classification described in Chap. 7. The source code, along with experiment results are located at

  https://github.com/gnodisnait/mushroom

[1]Funded by the Ministry of Education and Research of Germany (BMBF) under grant number 01/S17064.

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https://doi.org/10.1007/978-3-030-56275-5

Appendix B
Sample Task for Membership Validation

We describe a sample task of Sect. 6.5.4. In Word-Net 3.0, city.n.01 has 605 members. We choose 1% of the 605 members as known city names (7 city names marked as red, following the first #), the rest as unknown city names (598 city names marked as blue, following the second #). Additionally, we randomly choose 100 entities which are neither members of the city.n.01 nor members of hypernymies of city.n.01 (marked as cyan, following the third #), and randomly choose 100 words which does not exist in the knowledge graph (marked as purple, following the forth #). The content of a task text is listed as follows. Our n-ball method correctly predicts 594 unknown cities without recognising non-city as city. This results in 100% precision and 99% recall.

city.n.01#linz.n.01 cremona.n.01 winchester.n.01 fargo.n.01 philippi.n.01 atlanta.n.01 medan.n.01#bologna.n.01 medina.n.01 toulouse.n.01 zaragoza.n.01 tokyo.n.01 katsina.n.01 fez.n.01 melbourne.n.02 manchester.n.01 montpelier.n.01 huambo.n.01 maseru.n.01 ankara.n.01 tijuana.n.01 waco.n.01 lublin.n.01 salem.n.03 lome.n.01 springfield.n.03 kigali.n.01 minneapolis.n.01 aquila.n.02 kumasi.n.01 hohhot.n.01 liege.n.03 morgantown.n.01 wuhan.n.01 charlotte.n.01 taichung.n.01 tucson.n.01 shiraz.n.01 maiduguri.n.01 dhaka.n.01 rabat.n.01 lansing.n.01 plano.n.01 ljubljana.n.01 guantanamo.n.01 geneva.n.01 leipzig.n.01 toronto.n.01 campeche.n.01 albuquerque.n.01 cherepovets.n.01 harrisburg.n.01 novosibirsk.n.01 marrakesh.n.01 tacoma.n.01 windsor.n.01 moscow.n.01 fresno.n.01 madrid.n.01 karachi.n.01 quito.n.01 aswan.n.01 namur.n.01 chelyabinsk.n.01 sfax.n.01 blantyre.n.01 kimberley.n.01 kolonia.n.01 lund.n.01 newport.n.02 sparta.n.01 dayton.n.01 gulu.n.01 lille.n.01 omsk.n.01 salem.n.02 urmia.n.02 lancaster.n.01 hartford.n.01 valencia.n.01 leeds.n.01 zomba.n.01 samarkand.n.01 mumbai.n.01 tangshan.n.01 richmond.n.01 halicarnassus.n.01 goma.n.01 cordoba.n.03 bonn.n.01 bangalore.n.01 lhasa.n.01 nagoya.n.01 astana.n.01 bursa.n.01 nineveh.n.01 katowice.n.01 amarillo.n.01 maputo.n.01 waterbury.n.01 ephesus.n.01 ottawa.n.03 montreal.n.01 volgograd.n.01 charleston.n.

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https://doi.org/10.1007/978-3-030-56275-5

01 london.n.01 omaha.n.02 quebec.n.01 persepolis.n.01 pinsk.n.01 shenyang.n.01 toyota.n.01 versailles.n.01 milwaukee.n.01 kampala.n.01 valletta.n.01 louisville.n.01 soledad.n.01 brno.n.01 nakuru.n.01 lexington.n.02 jakarta.n.01 stockholm.n.01 riverside.n.02 worcester.n.02 apia.n.01 wheeling.n.01 lausanne.n.01 jackson.n.10 tabriz.n.01 singapore.n.01 ur.n.01 shreveport.n.01 augusta.n.02 bruges.n.01 augusta.n.01 hobart.n.01 blida.n.01 delhi.n.01 charleroi.n.01 tulsa.n.01 kuwait.n.01 mosul.n.01 kinshasa.n.01 raleigh.n.02 prague.n.01 braunschweig.n.01 caracas.n.01 malabo.n.01 binghamton.n.01 lucknow.n.01 taipei.n.01 huntington.n.04 xian.n.01 male.n.03 adelaide.n.01 kingstown.n.01 bern.n.01 scranton.n.01 portland.n.02 lincoln.n.02 tegucigalpa.n.01 venice.n.01 washington.n.01 jerusalem.n.01 taif.n.01 trento.n.01 split.n.06 trenton.n.01 vladivostok.n.01 aachen.n.01 juneau.n.01 mycenae.n.01 dobrich.n.01 suez.n.01 matamoros.n.01 soweto.n.01 jabalpur.n.01 dushanbe.n.01 leon.n.02 bolzano.n.01 nice.n.01 cali.n.01 babylon.n.01 novgorod.n.01 minsk.n.01 chemnitz.n.01 kaunas.n.01 hangzhou.n.01 pisa.n.01 bandung.n.01 st._petersburg.n.02 astrakhan.n.02 bratislava.n.01 yangon.n.01 banff.n.01 manila.n.02 arnhem.n.01 sacramento.n.01 munich.n.01 kananga.n.01 wroclaw.n.01 omdurman.n.01 brasilia.n.01 zabrze.n.01 bloemfontein.n.01 yaounde.n.01 yerevan.n.01 edmonton.n.01 delphi.n.01 topeka.n.01 paterson.n.02 khabarovsk.n.01 sapporo.n.01 pittsburgh.n.01 nancy.n.01 honolulu.n.01 columbus.n.01 guadalajara.n.01 bremen.n.01 nanning.n.01 temuco.n.01 pierre.n.01 jinja.n.01 lilongwe.n.01 antananarivo.n.01 gomorrah.n.01 boise.n.01 helena.n.01 cambridge.n.03 tepic.n.01 schenectady.n.01 limeira.n.01 victoria.n.07 solingen.n.01 casper.n.01 wurzburg.n.01 halle.n.01 bishkek.n.01 mesa.n.02 salem.n.01 gafsa.n.01 chernobyl.n.01 cheyenne.n.01 durango.n.01 samaria.n.01 flint.n.03 arequipa.n.01 seoul.n.01 annapolis.n.01 concord.n.01 fredericton.n.01 salzburg.n.01 nuremberg.n.01 nyala.n.01 cambridge.n.02 bissau.n.01 bamako.n.01 winnipeg.n.01 taegu.n.01 cleveland.n.01 brasov.n.01 abidjan.n.01 ostrava.n.01 lyon.n.01 potsdam.n.01 bangui.n.01 bakersfield.n.01 birmingham.n.01 rasht.n.01 curitiba.n.01 kabul.n.01 rosario.n.01 utrecht.n.01 independence.n.03 regina.n.01 rotterdam.n.01 timbuktu.n.01 peoria.n.01 tampere.n.01 villahermosa.n.01 nagano.n.01 olympia.n.01 kitakyushu.n.01 cologne.n.01 argos.n.01 rochester.n.01 tours.n.01 essen.n.01 dresden.n.01 kaluga.n.01 suva.n.01 daugavpils.n.01 indianapolis.n.01 beckley.n.01 troy.n.02 kandahar.n.01 wichita.n.02 pueblo.n.02 garland.n.02 hanoi.n.01 faisalabad.n.01 praia.n.01 paris.n.01 warszawa.n.01 concepcion.n.01 pergamum.n.01 lynchburg.n.01 tabuk.n.01 roseau.n.01 tartu.n.01 kishinev.n.01 providence.n.01 uppsala.n.01 brighton.n.01 thebes.n.01 arlington.n.01 reading.n.06 valencia.n.02 bogota.n.01 constantine.n.02 darwin.n.02 grenoble.n.01 apeldoorn.n.01 turin.n.01 kolkata.n.01 spokane.n.01 parkersburg.n.01 abuja.n.01 tarawa.n.01 bari.n.01 memphis.n.01 chattanooga.n.01 montevideo.n.01 baghdad.n.01 toyohashi.n.01 espoo.n.01 aberdeen.n.04 adana.n.01 cincinnati.n.01 newark.n.01 durham.n.01 rheims.n.01 bayonne.n.01 oviedo.n.01 huntsville.n.01 worcester.n.03 greensboro.n.01 utica.n.02 vienna.n.01 athens.n.01 fukuoka.n.01 winston-salem.n.01 edirne.n.01 lusaka.n.01 beijing.n.01 islamabad.n.01 tianjin.n.01 nashville.n.01 dover.n.01 austin.n.01 roanoke.n.01 mandalay.n.01 gaborone.n.01 orizaba.n.01 luxor.n.01 hamilton.n.06 assur.n.01 peshawar.n.01 brescia.n.01 mashhad.n.01 puebla.n.01 nalchik.n.01 anchorage.n.03 oaxaca.n.01 lanzhou.n.01 sydney.n.01 donetsk.n.01 merida.n.01 ariana.n.01 macon.n.01 kirkuk.

n.01 chihuahua.n.01 oxford.n.01 mazar-i-sharif.n.01 nicosia.n.01 genoa.n.01 manama.n.01 yalta.n.01 tripoli.n.02 isfahan.n.01 byzantium.n.01 vaduz.n.01 braga.n.01 camden.n.01 saratov.n.01 teheran.n.01 copenhagen.n.01 odessa.n.02 nicaea.n.01 leon.n.03 riyadh.n.01 gloucester.n.02 frankfort.n.01 allentown.n.01 johannesburg.n.01 springfield.n.01 knoxville.n.01 khartoum.n.01 caloocan.n.01 ufa.n.01 managua.n.01 birmingham.n.02 orlando.n.01 taiyuan.n.01 luoyang.n.01 bruxelles.n.01 guayaquil.n.01 osasco.n.01 qum.n.01 kandy.n.01 davenport.n.01 dodoma.n.01 verona.n.01 buffalo.n.02 billings.n.01 basseterre.n.01 almaty.n.01 albany.n.01 agra.n.01 weimar.n.01 leiden.n.01 tabora.n.01 zaria.n.01 lubeck.n.01 pyongyang.n.01 hyderabad.n.02 padua.n.01 springfield.n.02 sucre.n.02 firenze.n.01 lahore.n.01 oujda.n.01 amman.n.01 dallas.n.01 constantina.n.01 nijmegen.n.01 anaheim.n.01 bydgoszcz.n.01 medellin.n.01 libreville.n.01 amsterdam.n.01 lubbock.n.01 hyderabad.n.01 nairobi.n.01 innsbruck.n.01 giza.n.01 zurich.n.01 tbilisi.n.01 memphis.n.02 halifax.n.01 bam.n.01 decatur.n.02 granada.n.01 whitehorse.n.01 grozny.n.01 zagreb.n.01 cebu.n.01 madison.n.02 asmara.n.01 syracuse.n.01 kingston.n.03 smolensk.n.01 czestochowa.n.01 sheffield.n.01 pompeii.n.01 istanbul.n.01 nouakchott.n.01 toledo.n.02 leicester.n.02 christchurch.n.01 lima.n.01 nanchang.n.01 moron.n.02 toledo.n.01 eugene.n.02 evansville.n.01 nassau.n.01 cancun.n.01 kursk.n.01 rockford.n.01 abilene.n.01 rawalpindi.n.01 hermosillo.n.01 tamale.n.01 douala.n.01 tangier.n.01 sebastopol.n.01 kazan.n.02 philadelphia.n.01 cracow.n.01 lubumbashi.n.01 orleans.n.01 berkeley.n.02 mwanza.n.01 sana.n.01 chongqing.n.01 utica.n.01 windhoek.n.01 plovdiv.n.01 perth.n.01 omiya.n.01 saskatoon.n.01 sodom.n.02 maracay.n.01 eindhoven.n.01 coventry.n.02 papeete.n.01 vientiane.n.01 n'djamena.n.01 beaumont.n.03 nanjing.n.01 pretoria.n.01 skopje.n.01 akron.n.01 niamey.n.01 berlin.n.01 mannheim.n.01 sardis.n.01 herat.n.01 hargeisa.n.01 burlington.n.01 havana.n.01 wilmington.n.02 kathmandu.n.01 youngstown.n.01 tallahassee.n.01 bulawayo.n.01 manchester.n.02 boston.n.01 rostock.n.01 sudbury.n.01 graz.n.01 jerez.n.01 pasadena.n.01 brisbane.n.01 perm.n.01 harare.n.01 dnipropetrovsk.n.01 chennai.n.01 honiara.n.01 monterrey.n.01 provo.n.01 mysore.n.01 lodz.n.01 strasbourg.n.01 syracuse.n.02 ferrara.n.01 phoenix.n.01 accra.n.01 mexicali.n.01 ibadan.n.01 montgomery.n.03 milan.n.01 tirana.n.01 asahikawa.n.01 greenville.n.02 thebes.n.02 tashkent.n.01 calgary.n.01 putrajaya.n.01 mbeya.n.01 sofia.n.01 nablus.n.01 reno.n.01 canberra.n.01 racine.n.02 belgrade.n.01 bujumbura.n.01 herculaneum.n.01 basel.n.01 chester.n.01 rome.n.01 cordoba.n.04 clarksburg.n.01 stuttgart.n.01 northampton.n.01 port-au-prince.n.01 dortmund.n.01 brazzaville.n.01 wellington.n.02 bismarck.n.02 kharkov.n.01 charlottetown.n.01 mbabane.n.01 sarajevo.n.01 funafuti.n.01 columbia.n.03 colombo.n.01 vilnius.n.01 bucharest.n.01 kyoto.n.01 budapest.n.01 dijon.n.01 denver.n.01#stick.v.12 cartagena.n.01 malpighiaceae.n.01 genet.n.03 cowgirl.n.01 browse.n.03 aged.n.01 dialogue.n.03 heat.n.04 smoulder.n.01 operate.v.03 disarm.v.02 appearance.n.05 gunnery.n.01 reintegrate.v.01 works.n.04 defend.v.01 ebitda.n.01 feeder.n.06 associate.v.01 tytonidae.n.01 alabama.n.01 musial.n.01 liliuokalani.n.01 affirmation.n.03 cud.n.01 pass.n.08 mirror.v.01 station.n.05 dim.v.02 sled.v.01 rattan.n.03 clairvoyance.n.01 pontifex.n.01 separation.n.04 mortician.n.01 theorize.v.03 leeway.n.01 doubling.n.01 harrison.n.03 fossilize.v.02 advantage.n.03 hula.n.01 dewberry.n.02 exhibit.v.01 wilson.n.11 permu-

tation.n.04 xhosa.n.01 withdrawal.n.02 stanley.n.02 maricopa.n.01 touch.n.01 penitentiary.n.01 palau.n.02 load.v.03 thalweg.n.01 weather.v.03 overtime.n.02 fornix.n.02 slap.n.01 foundation.n.03 delusion.n.02 consolidation.n.01 squint.v.01 heloise.n.01 canker.n.01 woodcut.n.01 expedition.n.01 chink.n.01 djanet.n.01 forum.n.01 breakage.n.02 geek.n.01 sarawak.n.01 plank.v.02 permian.n.01 brugmansia.n.01 flare.n.09 invar.n.01 cashier.v.02 stagnation.n.01 dimness.n.02 gilbert.n.02 soil.n.02 anaphora.n.01 albatross.n.02 wingback.n.02 mashriq.n.01 fund.v.05 hypothalamus.n.01 nose.v.02 rainbow.n.02 salicylate.n.01 replication.n.04 italian.n.01 fanlight.n.03 occult.v.03 subvert.v.04 discipline.n.03 fullness.n.03#boozed optima tirpitz per kilometros fsb gunships maghribi poonam centa inputs evangelion papers befehlshaber battleline acimovic hid 869,000 gogic gladu dactyls switzerland-based caratinga 41-33 bodens etlis hillview ielemia kerslake evelin gun-type assir ternana moyers nanos el-p xserve gesualdo manoharan backburner cits dola jawless vellacott preservationists niya ska lynette 88-game rumours recognitions mataka eest chromatography-mass bindman mazzoli polyesters rap/sung unecessary anura innervisions expenses govindsamy colorado-based dobiegniew transitioning god-daughter tanintharyi teliasonera trivelli 94 kg rainfall loingsech magidsohn euro365 fantagraphics ehrhardt warneke nidal guugu kiffmeyer pills pro-french 2,500-acre talks 1/3rd maariv serbs mahseer lovebugs brè batak newa calke nubians siguen unenumerated 0-100 1,707 douglas-fir

Appendix C
Sample Results of Membership Validation

See Table C.1.

Table C.1 List of membership validation. Column A is the total number of children; Column B is the number of training set; TP represents the number of true-positive predictions; FP represents the number of false-positive predictions; FN represents the number of false-negative predictions

Hypernym	A	B	Unknown hyponym	TP	FP	FN	Precision	Recall
activity.n.01	70	14	calibration.n.01	55	0	1	1.0	0.98
battle.n.01	80	16	zama.n.01	58	0	6	1.0	0.91
battle.n.01	80	32	solferino.n.02	47	0	1	1.0	0.98
be.v.01	123	13	swim.v.04	110	0	0	1.0	1.0
change.n.03	77	16	movement.n.11	61	0	0	1.0	1.0
change.v.02	249	100	relax.v.07	148	0	1	1.0	0.99
change.v.02	249	150	fall.v.26	99	0	0	1.0	1.0
city.n.01	605	7	bologna.n.01	594	0	4	1.0	0.99
city.n.01	605	545	juneau.n.01	60	0	0	1.0	1.0
communication.n.02	70	1	catch.n.05	20	0	49	1.0	0.29
composer.n.01	95	86	thomson.n.01	9	0	0	1.0	1.0
compound.n.02	110	2	methionine.n.01	72	0	36	1.0	0.67
compound.n.02	110	6	phenylalanine.n.01	91	0	13	1.0	0.88
condition.n.01	185	74	depression.n.01	111	0	0	1.0	1.0
country.n.02	167	9	georgia.n.03	146	0	12	1.0	0.92
cover.v.01	78	39	bread.v.01	39	0	0	1.0	1.0
deity.n.01	237	12	fortuna.n.01	179	0	46	1.0	0.8
deity.n.01	237	166	kartikeya.n.01	70	0	1	1.0	0.99
disease.n.01	92	37	poliomyelitis.n.01	55	0	0	1.0	1.0

(continued)

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https://doi.org/10.1007/978-3-030-56275-5

Table C.1 (continued)

Hypernym	A	B	Unknown hyponym	TP	FP	FN	Precision	Recall
european.n.01	72	8	norwegian.n.01	63	0	1	1.0	0.98
fabric.n.01	99	60	tammy.n.01	39	0	0	1.0	1.0
fabric.n.01	99	70	worsted.n.01	29	0	0	1.0	1.0
family.n.06	174	9	rubiaceae.n.01	161	0	4	1.0	0.98
fish.n.01	104	42	snapper.n.04	62	0	0	1.0	1.0
fish.n.01	104	52	menhaden.n.01	51	0	1	1.0	0.98
fish.n.01	104	84	sheepshead.n.01	20	0	0	1.0	1.0
genus.n.02	491	148	cycas.n.01	343	0	0	1.0	1.0
group.n.01	109	2	multitude.n.03	59	0	48	1.0	0.55
group.n.01	109	99	superfamily.n.01	10	0	0	1.0	1.0
herb.n.01	111	2	legume.n.01	87	0	22	1.0	0.8
herb.n.01	111	56	oregano.n.01	54	0	1	1.0	0.98
herb.n.01	111	100	caraway.n.01	11	0	0	1.0	1.0
instrument.n.01	73	1	probe.n.02	57	0	15	1.0	0.79
instrument.n.01	73	22	spectrograph.n.01	46	0	5	1.0	0.9
island.n.01	102	72	taiwan.n.02	30	0	0	1.0	1.0
letter.n.02	70	4	y.n.02	61	0	5	1.0	0.92
letter.n.02	70	35	theta.n.01	35	0	0	1.0	1.0
letter.n.02	70	42	r.n.03	28	0	0	1.0	1.0
material.n.01	80	32	earth.n.02	47	0	1	1.0	0.98
material.n.01	80	40	pigment.n.02	40	0	0	1.0	1.0
move.v.02	87	1	turn.v.04	13	0	73	1.0	0.15
move.v.02	87	35	rock.v.02	49	0	3	1.0	0.94
move.v.03	88	80	jump.v.01	8	0	0	1.0	1.0
music.n.01	91	1	tune.n.01	88	0	2	1.0	0.98
music.n.01	91	64	rap.n.05	27	0	0	1.0	1.0
object.n.01	73	59	cave.n.01	14	0	0	1.0	1.0
person.n.01	431	345	literate.n.01	86	0	0	1.0	1.0
phenomenon.n.01	93	28	exchange.n.01	61	0	4	1.0	0.94
physicist.n.01	116	12	sakharov.n.01	94	0	10	1.0	0.9
physicist.n.01	116	105	frisch.n.01	11	0	0	1.0	1.0
plant.n.02	70	49	shrub.n.01	21	0	0	1.0	1.0
plant.n.02	70	56	endemic.n.02	14	0	0	1.0	1.0
plant.n.02	70	63	ramp.n.02	7	0	0	1.0	1.0
port.n.01	153	62	haiphong.n.01	91	0	0	1.0	1.0
process.n.06	250	50	precipitation.n.02	199	0	1	1.0	0.99
process.n.06	250	125	inversion.n.03	125	0	0	1.0	1.0
process.n.06	250	225	phenomenon.n.01	25	0	0	1.0	1.0
remove.v.01	79	32	condense.v.03	47	0	0	1.0	1.0
remove.v.01	79	40	bone.v.02	39	0	0	1.0	1.0
remove.v.01	79	56	wash.v.09	23	0	0	1.0	1.0

(continued)

Table C.1 (continued)

Hypernym	A	B	Unknown hyponym	TP	FP	FN	Precision	Recall
river.n.01	154	47	scheldt.n.01	104	0	3	1.0	0.97
river.n.01	154	62	yalu.n.01	90	0	2	1.0	0.98
shrub.n.01	76	61	blackthorn.n.01	15	0	0	1.0	1.0
state.n.01	94	66	gujarat.n.02	28	0	0	1.0	1.0
state.n.02	77	24	sale.n.04	53	0	0	1.0	1.0
statesman.n.01	99	80	bacon.n.03	19	0	0	1.0	1.0
structure.n.04	72	15	nail.n.01	56	0	1	1.0	0.98
structure.n.04	72	58	nail.n.01	14	0	0	1.0	1.0
substance.n.01	107	22	selenium.n.01	82	0	3	1.0	0.96
supply.v.01	79	48	curtain.v.01	30	0	1	1.0	0.97
supply.v.01	79	72	dado.v.01	7	0	0	1.0	1.0
town.n.01	222	12	jackson.n.08	202	0	8	1.0	0.96
town.n.01	222	156	nogales.n.01	66	0	0	1.0	1.0
travel.v.01	112	34	pursue.v.02	78	0	0	1.0	1.0
whole.n.02	99	10	septum.n.02	89	0	0	1.0	1.0
whole.n.02	99	40	annulus.n.02	59	0	0	1.0	1.0
writer.n.01	344	35	malory.n.01	306	0	3	1.0	0.99
writer.n.01	344	207	hemingway.n.01	137	0	0	1.0	1.0
writer.n.01	344	241	mitchell.n.04	103	0	0	1.0	1.0

Appendix D
The Nine Laws of Cognition

- *First Law of Cognition: There are no benefits without costs* (Tversky 2019, pp. 15, 39, 51, 53, 150, 240).
- *Second Law of Cognition: Action molds perception* (Tversky 2019, p. 18).
- *Third Law of Cognition: Feeling comes first* (Tversky 2019, p. 42).
- *Fourth Law of Cognition: The mind can override perception* (Tversky 2019, pp. 55, 64).
- *Fifth Law of Cognition: Cognition mirrors perception* (Tversky 2019, pp. 57, 73, 81).
- *Sixth Law of Cognition: Spatial thinking is the foundation of abstract thought* (Tversky 2019, pp. 72, 142).
- *Seven Law of Cognition: The mind fills in missing information* (Tversky 2019, pp.78, 244).
- *Eighth Law of Cognition: When thought overflows the mind, the mind puts it into the world* (Tversky 2019, p. 190).
- *Ninth Law of Cognition: We organize the stuff in the world the way we organize the stuff in the mind* (Tversky 2019, p. 280).

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https://doi.org/10.1007/978-3-030-56275-5

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