boodleAI

Artificial Intelligence 101 for Nonprofits

Artificial Intelligence. Machine Learning. Data.

Introduction

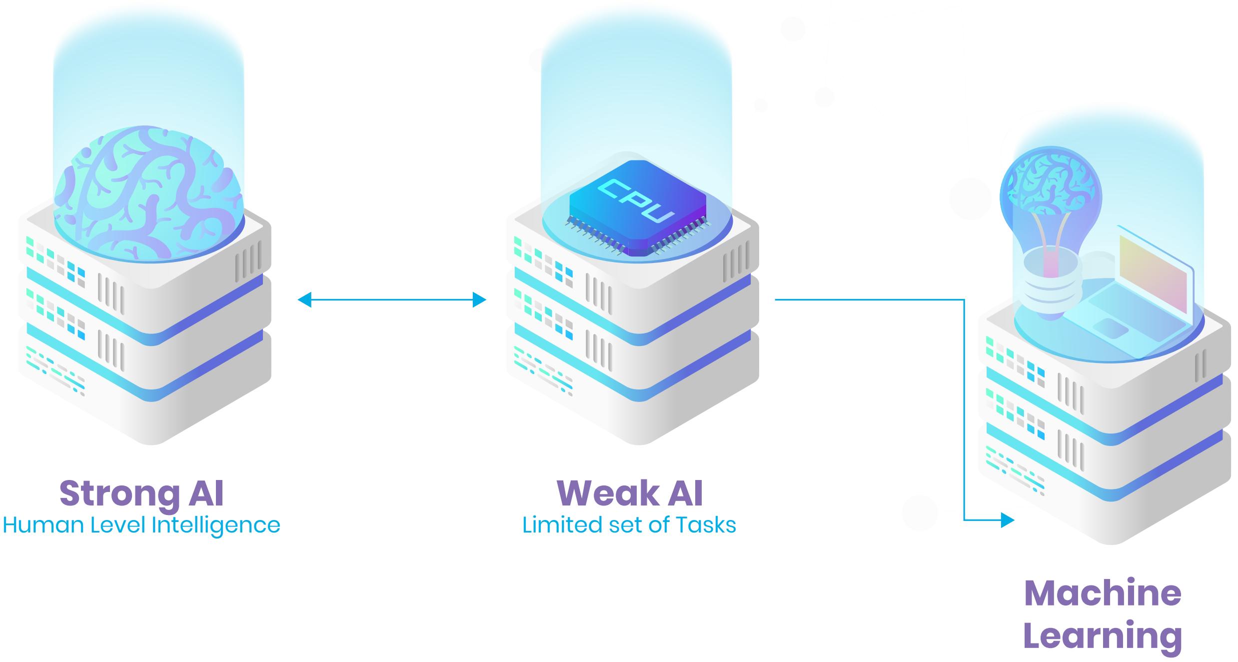
Nonprofit professionals hear the term Artificial Intelligence and realize that change is coming. What they may not realize is that this change will dramatically transform their world. The successful nonprofits of tomorrow will be the ones who invest time and money today to understand and embrace AI, machine learning, and data science.

But what do these terms actually mean? And how can nonprofit professionals make sense of the technologies and services powered by them and discern which, if any, are applicable to their organizational needs?

This white paper provides a primer for nonprofit professionals to understand the fundamentals of artificial intelligence (and its subset, machine learning), how they work, and how to evaluate and categorize AI technology they may encounter.

So, buckle up, and let's take a quick tour of tomorrow's nonprofit technology today.

What is Artificial Intelligence?



Many definitions of **artificial intelligence** exist[1], but they all describe AI as *a program that acts and thinks in ways that resemble intelligent humans*[2]. This type of AI program is often called an "**agent**." In this article, we'll use the term "**AI assistant**." AI is broadly split into two categories. The first is artificial general intelligence, otherwise known as "**Strong AI**," which, if it existed, would be AI assistants with *human-level intelligence*. This is currently the realm of futurists and science fiction. The second category is artificial narrow intelligence, otherwise known as "**Weak AI**," which is what we have today. *Weak AI assistants perform a limited set of tasks* (perhaps only one) such as speech recognition, autonomous driving, or flash trading. One subcategory of Weak AI is **machine learning**.

[1] One of the author's favorites is this one: artificial intelligence is "a system that perceives its environment and takes actions that maximize its chances of success." See https://en.wikiquote.org/wiki/Artificial_intelligence.

[2] A lot of debate exists about what AI is and isn't and whether the term is overused and inaccurately used. We'll just run with this definition for this article, even if it's subject to debate.

Machine Learning Requirements: What is Machine Learning?

Machine Learning is the most common subset of AI. Simply defined, Machine Learning *allows AI assistants to learn from data without human intervention.* It requires four components[3] : (1) data (2) models/algorithms; (3) tools/infrastructure; and (4) computing power.

Data **Algorithms/Models** **Tools/Infrastructure** **Computing Power**

1. **Data.** This is the most critical element. Without relevant data, machine learning is not possible. A **data set** generally consists of rows of "**observations**" or "**instances**" of information. For nonprofits, these are most often records of individual contacts or donations.

    Example: Nonprofit ABC has a wildly successful bike-a-thon supported by an industrial strength peer-to-peer fundraising program. Nonprofit ABC has datasets (in the form of excel spreadsheets) showing race participants (fundraisers), race supporters (donors), and those invited to fundraise or donate but who declined. Each spreadsheet row containing a person's record is an "observation" or "instance" of information in the dataset.

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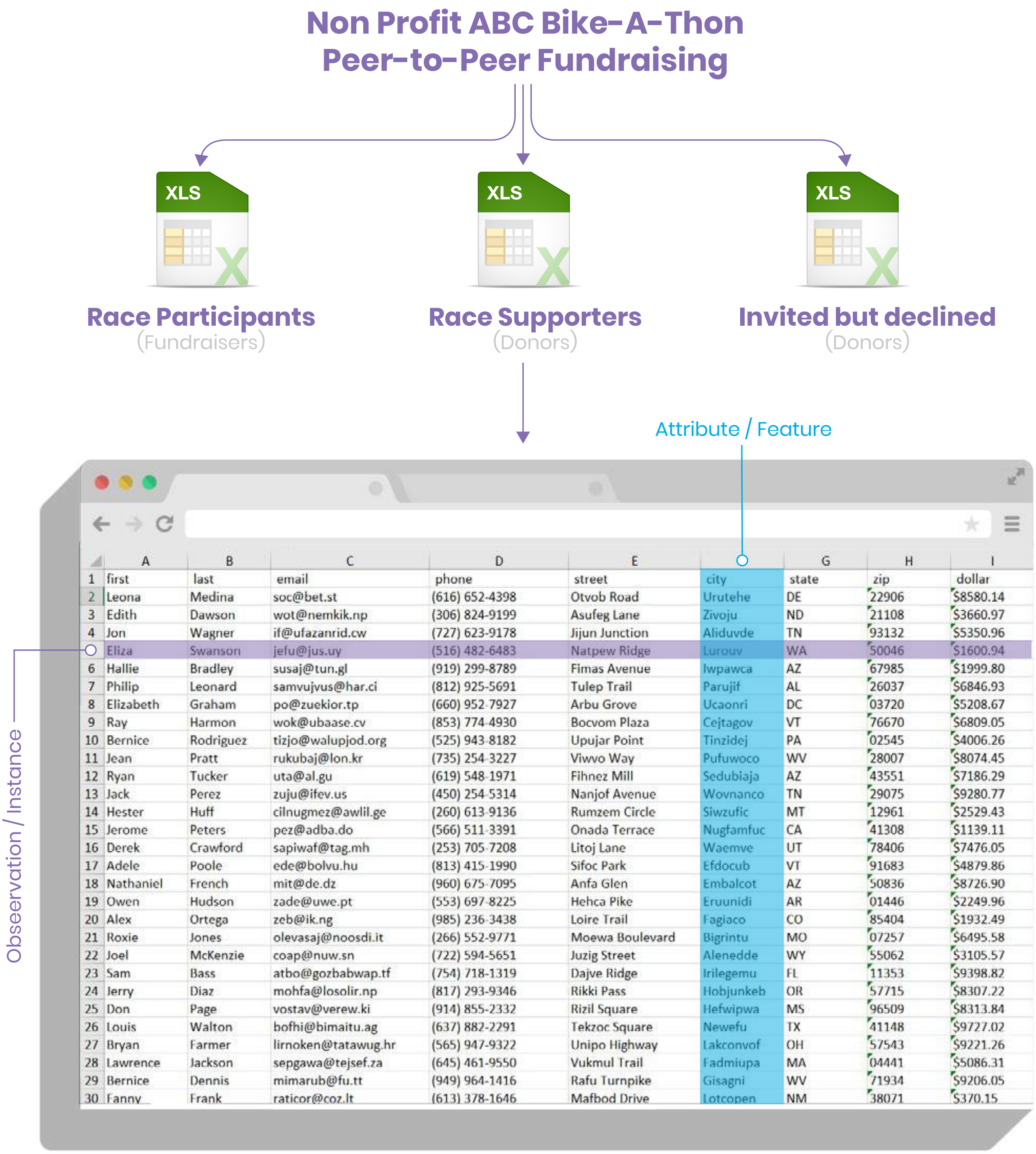
[3] https://medium.com/machine-learning-for-humans/why-machine-learning-matters-6164faf1df12



	A	B	C	D	E		G	H	I
1	first	last	email	phone	street	city	state	zip	dollar
2	Leona	Medina	soc@bet.st	(616) 652-4398	Otvob Road	Urutehe	DE	22906	$8580.14
3	Edith	Dawson	wot@nemkik.np	(306) 824-9199	Asufeg Lane	Zivoju	ND	21108	$3660.97
4	Jon	Wagner	if@ufazanrid.cw	(727) 623-9178	Jijun Junction	Aliduvde	TN	93132	$5350.96
	Eliza	Swanson	jefu@jus.uy	(516) 482-6483	Natpew Ridge	Lurouv	WA	50046	$1600.94
6	Hallie	Bradley	susaj@tun.gl	(919) 299-8789	Fimas Avenue	Iwpawca	AZ	67985	$1999.80
7	Philip	Leonard	samvujvus@har.ci	(812) 925-5691	Tulep Trail	Parujif	AL	26037	$6846.93
8	Elizabeth	Graham	po@zuekior.tp	(660) 952-7927	Arbu Grove	Ucaonri	DC	03720	$5208.67
9	Ray	Harmon	wok@ubaase.cv	(853) 774-4930	Bocvom Plaza	Cejtagov	VT	76670	$6809.05
10	Bernice	Rodriguez	tizjo@walupjod.org	(525) 943-8182	Upujar Point	Tinzidej	PA	02545	$4006.26
11	Jean	Pratt	rukubaj@lon.kr	(735) 254-3227	Viwvo Way	Pufuwoco	WV	28007	$8074.45
12	Ryan	Tucker	uta@al.gu	(619) 548-1971	Fihnez Mill	Sedubiaja	AZ	43551	$7186.29
13	Jack	Perez	zuju@ifev.us	(450) 254-5314	Nanjof Avenue	Wovnanco	TN	29075	$9280.77
14	Hester	Huff	cilnugmez@awlil.ge	(260) 613-9136	Rumzem Circle	Siwzufic	MT	12961	$2529.43
15	Jerome	Peters	pez@adba.do	(566) 511-3391	Onada Terrace	Nugfamfuc	CA	41308	$1139.11
16	Derek	Crawford	sapiwaf@tag.mh	(253) 705-7208	Litoj Lane	Waemve	UT	78406	$7476.05
17	Adele	Poole	ede@bolvu.hu	(813) 415-1990	Sifoc Park	Efdocub	VT	91683	$4879.86
18	Nathaniel	French	mit@de.dz	(960) 675-7095	Anfa Glen	Embalcot	AZ	50836	$8726.90
19	Owen	Hudson	zade@uwe.pt	(553) 697-8225	Hehca Pike	Eruunidi	AR	01446	$2249.96
20	Alex	Ortega	zeb@ik.ng	(985) 236-3438	Loire Trail	Fagiaco	CO	85404	$1932.49
21	Roxie	Jones	olevasaj@noosdi.it	(266) 552-9771	Moewa Boulevard	Bigrintu	MO	07257	$6495.58
22	Joel	McKenzie	coap@nuw.sn	(722) 594-5651	Juzig Street	Alenedde	WY	55062	$3105.57
23	Sam	Bass	atbo@gozbabwap.tf	(754) 718-1319	Dajve Ridge	Irilegemu	FL	11353	$9398.82
24	Jerry	Diaz	mohfa@losolir.np	(817) 293-9346	Rikki Pass	Hobjunkeb	OR	57715	$8307.22
25	Don	Page	vostav@verew.ki	(914) 855-2332	Rizil Square	Hefwipwa	MS	96509	$8313.84
26	Louis	Walton	bofhi@bimaitu.ag	(637) 882-2291	Tekzoc Square	Newefu	TX	41148	$9727.02
27	Bryan	Farmer	lirnoken@tatawug.hr	(565) 947-9322	Unipo Highway	Lakconvof	OH	57543	$9221.26
28	Lawrence	Jackson	sepgawa@tejsef.za	(645) 461-9550	Vukmul Trail	Fadmiupa	MA	04441	$5086.31
29	Bernice	Dennis	mimarub@fu.tt	(949) 964-1416	Rafu Turnpike	Gisagni	WV	71934	$9206.05
30	Fanny	Frank	raticor@coz.lt	(613) 378-1646	Mafbod Drive	Lotcopen	NM	38071	$370.15

For each observation or instance, the data set contains "**attributes**" or "**features**," which are specific categories of information that describe a record[4].

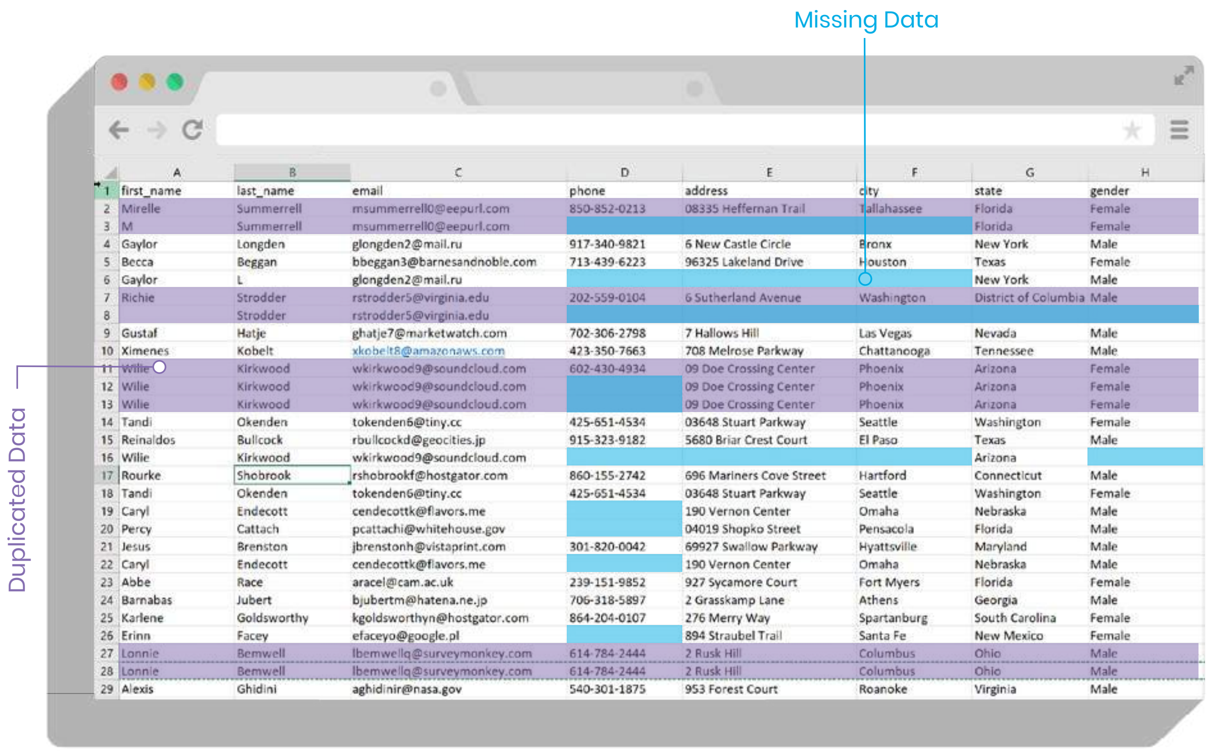
> *Example: Nonprofit ABC's bike-a-thon dataset of donors for last year contains each donor's first name, last name, email address, phone number, address, and amount donated. Each of these columns is an "attribute" or "feature".*

[4] https://ml-cheatsheet.readthedocs.io/en/latest/glossary.html#glossary-model

The **dimensions** of a data set are the number of **features** it has.

Example: Nonprofit ABC's bike-a-thon dataset described above has 9 features, so it has 9 dimensions.

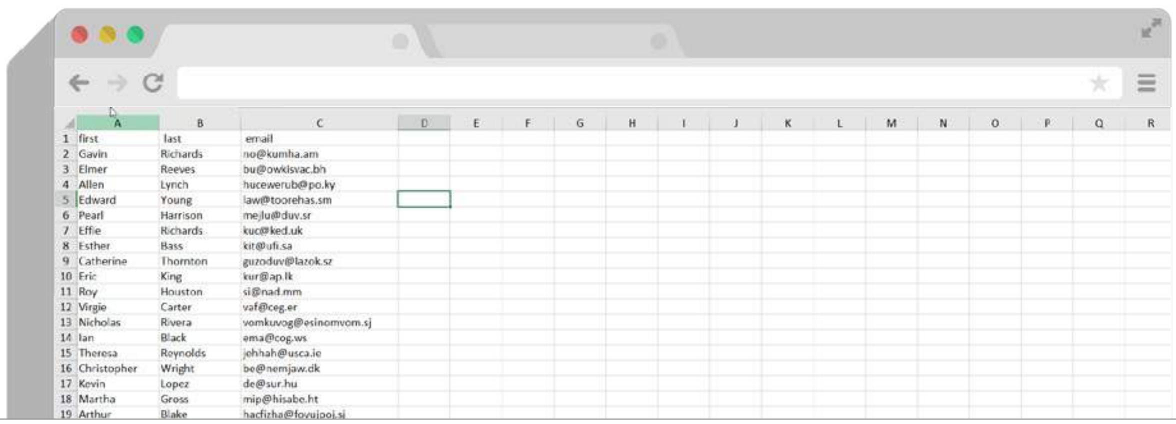
Unfortunately, nonprofits often lack the right kind of data for machine learning by AI assistants. Nonprofit data is often "**messy**" with duplicate records and information missing from records[5].



	A	B	C	D	E	F	G	H
1	first_name	last_name	email	phone	address	city	state	gender
2	Mirelle	Summerrell	msummerrell0@eepurl.com	850-852-0213	08335 Heffernan Trail	Tallahassee	Florida	Female
3	M	Summerrell	msummerrell0@eepurl.com				Florida	Female
4	Gaylor	Longden	glongden2@mail.ru	917-340-9821	6 New Castle Circle	Bronx	New York	Male
5	Becca	Beggan	bbeggan3@barnesandnoble.com	713-439-6223	96325 Lakeland Drive	Houston	Texas	Female
6	Gaylor	L	glongden2@mail.ru				New York	Male
7	Richie	Strodder	rstrodder5@virginia.edu	202-559-0104	6 Sutherland Avenue	Washington	District of Columbia	Male
8		Strodder	rstrodder5@virginia.edu					
9	Gustaf	Hatje	ghatje7@marketwatch.com	702-306-2798	7 Hallows Hill	Las Vegas	Nevada	Male
10	Ximenes	Kobelt	xkobelt8@amazonaws.com	423-350-7663	708 Melrose Parkway	Chattanooga	Tennessee	Male
11	Wilie	Kirkwood	wkirkwood9@soundcloud.com	602-430-4934	09 Doe Crossing Center	Phoenix	Arizona	Female
12	Wilie	Kirkwood	wkirkwood9@soundcloud.com		09 Doe Crossing Center	Phoenix	Arizona	Female
13	Wilie	Kirkwood	wkirkwood9@soundcloud.com		09 Doe Crossing Center	Phoenix	Arizona	Female
14	Tandi	Okenden	tokenden6@tiny.cc	425-651-4534	03648 Stuart Parkway	Seattle	Washington	Female
15	Reinaldos	Bullcock	rbullcockd@geocities.jp	915-323-9182	5680 Briar Crest Court	El Paso	Texas	Male
16	Wilie	Kirkwood	wkirkwood9@soundcloud.com				Arizona	
17	Rourke	Shobrook	rshobrookf@hostgator.com	860-155-2742	696 Mariners Cove Street	Hartford	Connecticut	Male
18	Tandi	Okenden	tokenden6@tiny.cc	425-651-4534	03648 Stuart Parkway	Seattle	Washington	Female
19	Caryl	Endecott	cendecottk@flavors.me		190 Vernon Center	Omaha	Nebraska	Male
20	Percy	Cattach	pcattachi@whitehouse.gov		04019 Shopko Street	Pensacola	Florida	Male
21	Jesus	Brenston	jbrenstonh@vistaprint.com	301-820-0042	69927 Swallow Parkway	Hyattsville	Maryland	Male
22	Caryl	Endecott	cendecottk@flavors.me		190 Vernon Center	Omaha	Nebraska	Male
23	Abbe	Race	aracel@cam.ac.uk	239-151-9852	927 Sycamore Court	Fort Myers	Florida	Female
24	Barnabas	Jubert	bjubertm@hatena.ne.jp	706-318-5897	2 Grasskamp Lane	Athens	Georgia	Male
25	Karlene	Goldsworthy	kgoldsworthyn@hostgator.com	864-204-0107	276 Merry Way	Spartanburg	South Carolina	Female
26	Erinn	Facey	efaceyo@google.pl		894 Straubel Trail	Santa Fe	New Mexico	Female
27	Lonnie	Bemwell	lbemwellq@surveymonkey.com	614-784-2444	2 Rusk Hill	Columbus	Ohio	Male
28	Lonnie	Bemwell	lbemwellq@surveymonkey.com	614-784-2444	2 Rusk Hill	Columbus	Ohio	Male
29	Alexis	Ghidini	aghidinir@nasa.gov	540-301-1875	953 Forest Court	Roanoke	Virginia	Male

Nonprofit data may be too "**skinny**" (i.e. there isn't much data about each record).

Example: Nonprofit ABC's dataset of those invited to fundraise or donate but who declined contains only each individual's first name, last name, and email address. This is a skinny dataset.

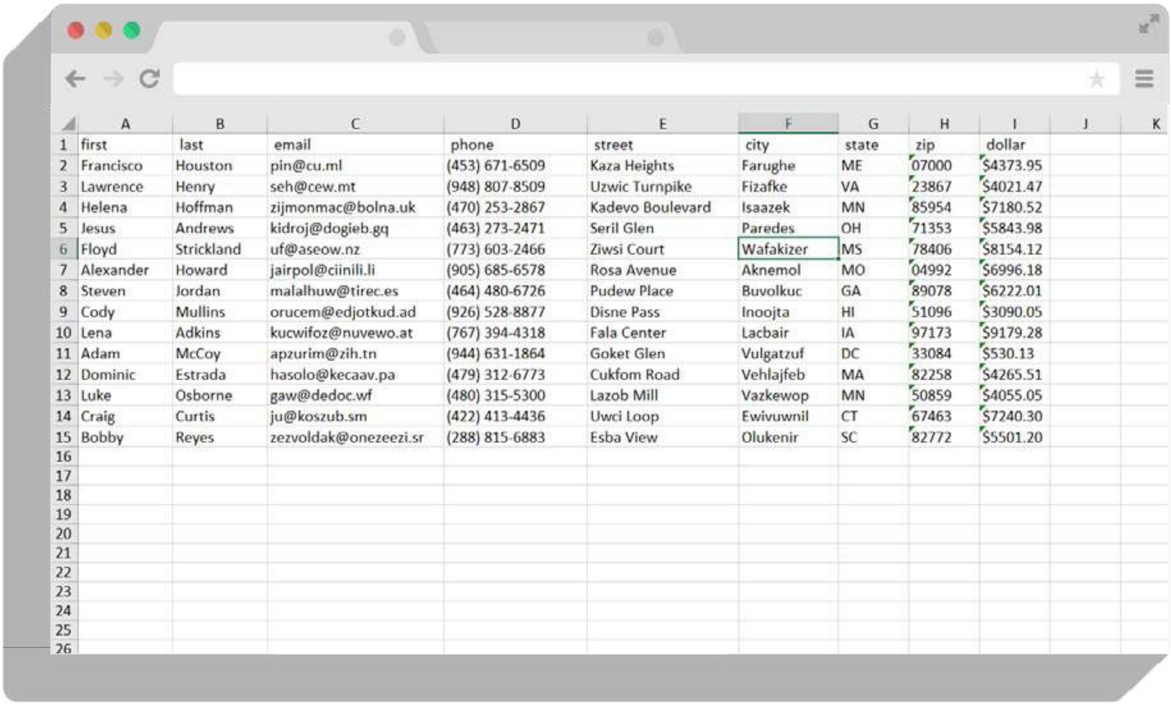


	A	B	C
1	first	last	email
2	Gavin	Richards	no@kumha.am
3	Elmer	Reeves	bu@owkisvac.bh
4	Allen	Lynch	hucewerub@po.ky
5	Edward	Young	law@toorehas.sm
6	Pearl	Harrison	mejlu@duv.sr
7	Effie	Richards	kuc@ked.uk
8	Esther	Bass	kit@ufi.sa
9	Catherine	Thornton	guzoduv@lazok.sz
10	Eric	King	kur@ap.lk
11	Roy	Houston	si@nad.mm
12	Virgie	Carter	vaf@ceg.er
13	Nicholas	Rivera	vomkuvog@esinomvom.sj
14	Ian	Black	ema@cog.ws
15	Theresa	Reynolds	jehhah@usca.ie
16	Christopher	Wright	be@nemjaw.dk
17	Kevin	Lopez	de@sur.hu
18	Martha	Gross	mip@hisabe.ht
19	Arthur	Blake	hacfizha@fovujooi.sj

[5] https://towardsdatascience.com/artificial-intelligence-and-bad-data-fbf2564c541a

Or, a nonprofit data set may too "**short**". Meaning, there aren't enough contact records.[6]

> *Example: Nonprofit ABC's first year running a bike-a-thon had a disappointing turnout of 14 participants who gathered 47 donations. That's a short dataset (and a development director's nightmare).*

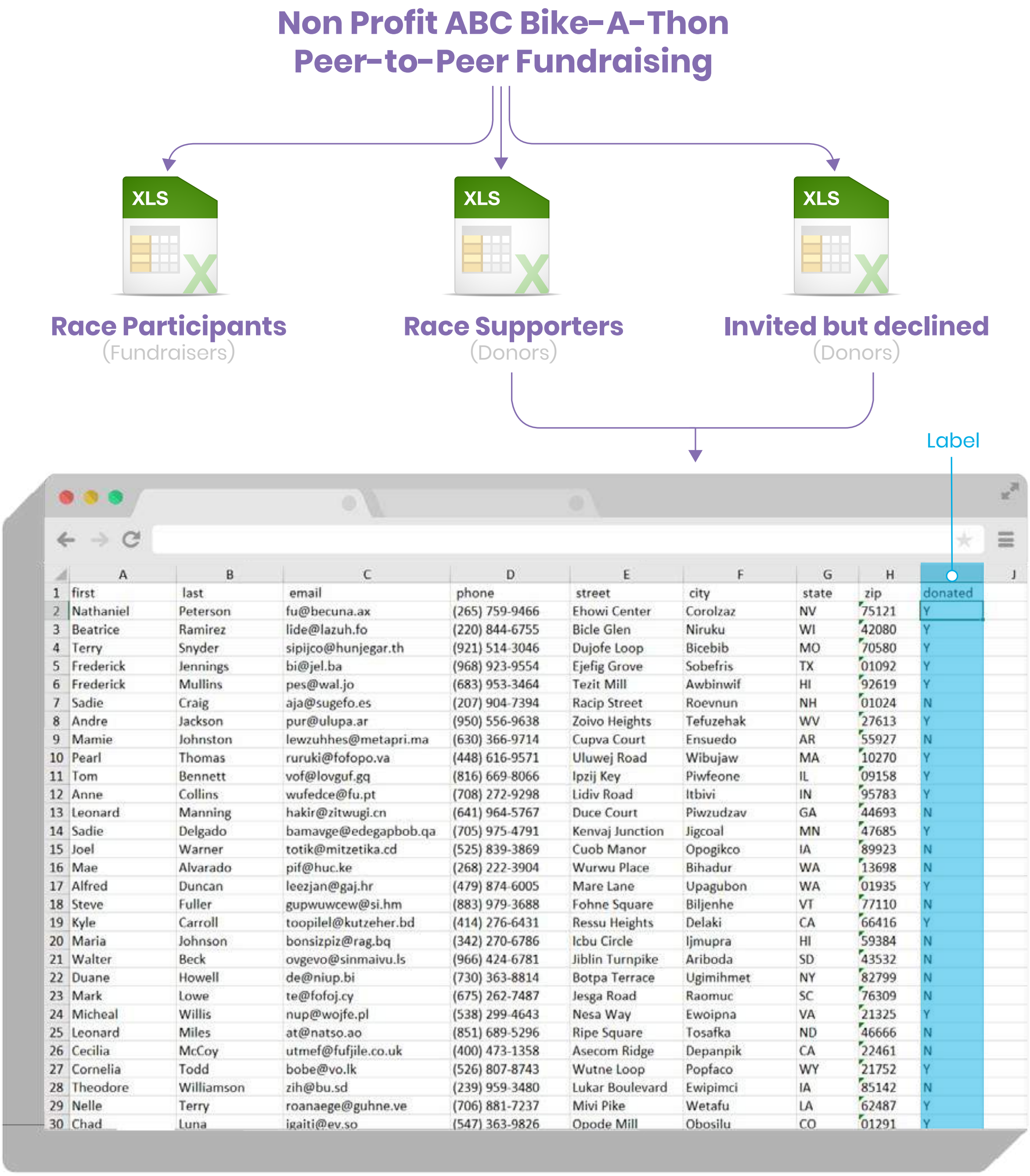


	first	last	email	phone	street	city	state	zip	dollar
2	Francisco	Houston	pin@cu.ml	(453) 671-6509	Kaza Heights	Farughe	ME	07000	$4373.95
3	Lawrence	Henry	seh@cew.mt	(948) 807-8509	Uzwic Turnpike	Fizafke	VA	23867	$4021.47
4	Helena	Hoffman	zijmonmac@bolna.uk	(470) 253-2867	Kadevo Boulevard	Isaazek	MN	85954	$7180.52
5	Jesus	Andrews	kidroj@dogieb.gq	(463) 273-2471	Seril Glen	Paredes	OH	71353	$5843.98
6	Floyd	Strickland	uf@aseow.nz	(773) 603-2466	Ziwsi Court	Wafakizer	MS	78406	$8154.12
7	Alexander	Howard	jairpol@ciinili.li	(905) 685-6578	Rosa Avenue	Aknemol	MO	04992	$6996.18
8	Steven	Jordan	malalhuw@tirec.es	(464) 480-6726	Pudew Place	Buvolkuc	GA	89078	$6222.01
9	Cody	Mullins	orucem@edjotkud.ad	(926) 528-8877	Disne Pass	Inoojta	HI	51096	$3090.05
10	Lena	Adkins	kucwifoz@nuvewo.at	(767) 394-4318	Fala Center	Lacbair	IA	97173	$9179.28
11	Adam	McCoy	apzurim@zih.tn	(944) 631-1864	Goket Glen	Vulgatzuf	DC	33084	$530.13
12	Dominic	Estrada	hasolo@kecaav.pa	(479) 312-6773	Cukfom Road	Vehlajfeb	MA	82258	$4265.51
13	Luke	Osborne	gaw@dedoc.wf	(480) 315-5300	Lazob Mill	Vazkewop	MN	50859	$4055.05
14	Craig	Curtis	ju@koszub.sm	(422) 413-4436	Uwci Loop	Ewivuwnil	CT	67463	$7240.30
15	Bobby	Reyes	zezvoldak@onezeezi.sr	(288) 815-6883	Esba View	Olukenir	SC	82772	$5501.20

And for many types of machine learning algorithms, the nonprofit data must be accurately **labeled.**

> *Example: Nonprofit ABC wants to train an AI Assistant to identify individuals who are most likely to donate to this year's upcoming bike-a-thon. This would require a dataset of contacts previously asked to donate to Nonprofit ABC's bike-a-thon, and whether or not the contact actually donated (pssst---that's the label). Fortunately, Nonprofit ABC has that dataset by combining the lists of those who donated and those invited to donate and declined (it will still need to figure out how to get past its skinny data problem, though!).*

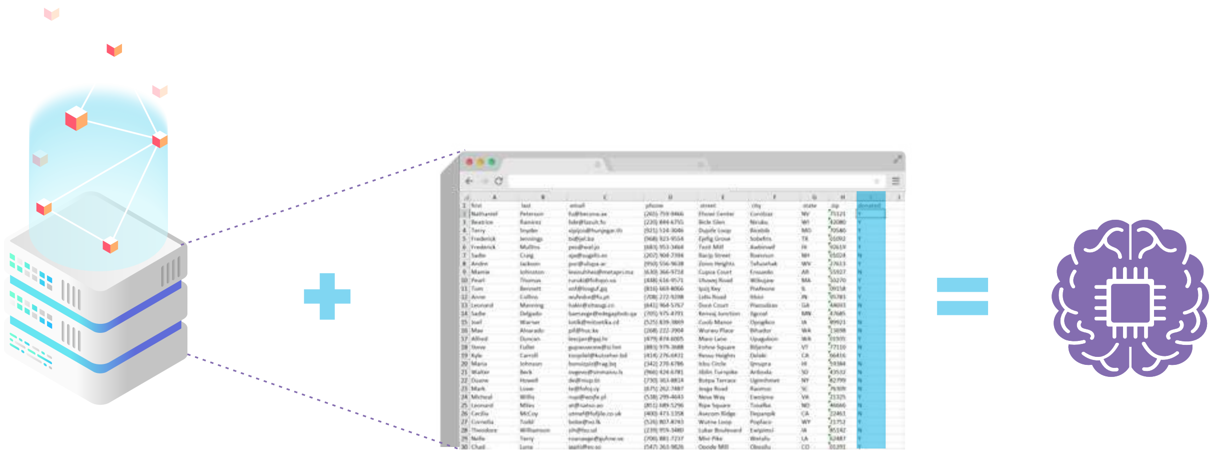
[6] https://blogs.sas.com/content/sastraining/2018/05/07/wide-versus-tall-data-proc-transpose-v-the-data-step/ Note skinny and short are simply opposites of wide and tall data.



	A	B	C	D	E	F	G	H		J
1	first	last	email	phone	street	city	state	zip	donated	
2	Nathaniel	Peterson	fu@becuna.ax	(265) 759-9466	Ehowi Center	Corolzaz	NV	75121	Y	
3	Beatrice	Ramirez	lide@lazuh.fo	(220) 844-6755	Bicle Glen	Niruku	WI	42080	Y	
4	Terry	Snyder	sipijco@hunjegar.th	(921) 514-3046	Dujofe Loop	Bicebib	MO	70580	Y	
5	Frederick	Jennings	bi@jel.ba	(968) 923-9554	Ejefig Grove	Sobefris	TX	01092	Y	
6	Frederick	Mullins	pes@wal.jo	(683) 953-3464	Tezit Mill	Awbinwif	HI	92619	Y	
7	Sadie	Craig	aja@sugefo.es	(207) 904-7394	Racip Street	Roevnun	NH	01024	N	
8	Andre	Jackson	pur@ulupa.ar	(950) 556-9638	Zoivo Heights	Tefuzehak	WV	27613	Y	
9	Mamie	Johnston	lewzuhhes@metapri.ma	(630) 366-9714	Cupva Court	Ensuedo	AR	55927	N	
10	Pearl	Thomas	ruruki@fofopo.va	(448) 616-9571	Uluwej Road	Wibujaw	MA	10270	Y	
11	Tom	Bennett	vof@lovguf.gq	(816) 669-8066	Ipzij Key	Piwfeone	IL	09158	Y	
12	Anne	Collins	wufedce@fu.pt	(708) 272-9298	Lidiv Road	Itbivi	IN	95783	Y	
13	Leonard	Manning	hakir@zitwugi.cn	(641) 964-5767	Duce Court	Piwzudzav	GA	44693	N	
14	Sadie	Delgado	bamavge@edegapbob.qa	(705) 975-4791	Kenvaj Junction	Jigcoal	MN	47685	Y	
15	Joel	Warner	totik@mitzetika.cd	(525) 839-3869	Cuob Manor	Opogikco	IA	89923	N	
16	Mae	Alvarado	pif@huc.ke	(268) 222-3904	Wurwu Place	Bihadur	WA	13698	N	
17	Alfred	Duncan	leezjan@gaj.hr	(479) 874-6005	Mare Lane	Upagubon	WA	01935	Y	
18	Steve	Fuller	gupwuwcew@si.hm	(883) 979-3688	Fohne Square	Biljenhe	VT	77110	N	
19	Kyle	Carroll	toopilel@kutzeher.bd	(414) 276-6431	Ressu Heights	Delaki	CA	66416	Y	
20	Maria	Johnson	bonsizpiz@rag.bq	(342) 270-6786	Icbu Circle	Ijmupra	HI	59384	N	
21	Walter	Beck	ovgevo@sinmaivu.ls	(966) 424-6781	Jiblin Turnpike	Ariboda	SD	43532	N	
22	Duane	Howell	de@niup.bi	(730) 363-8814	Botpa Terrace	Ugimihmet	NY	82799	N	
23	Mark	Lowe	te@fofoj.cy	(675) 262-7487	Jesga Road	Raomuc	SC	76309	N	
24	Micheal	Willis	nup@wojfe.pl	(538) 299-4643	Nesa Way	Ewoipna	VA	21325	Y	
25	Leonard	Miles	at@natso.ao	(851) 689-5296	Ripe Square	Tosafka	ND	46666	N	
26	Cecilia	McCoy	utmef@fufjile.co.uk	(400) 473-1358	Asecom Ridge	Depanpik	CA	22461	N	
27	Cornelia	Todd	bobe@vo.lk	(526) 807-8743	Wutne Loop	Popfaco	WY	21752	Y	
28	Theodore	Williamson	zih@bu.sd	(239) 959-3480	Lukar Boulevard	Ewipimci	IA	85142	N	
29	Nelle	Terry	roanaege@guhne.ve	(706) 881-7237	Mivi Pike	Wetafu	LA	62487	Y	
30	Chad	Luna	igaiti@ev.so	(547) 363-9826	Opode Mill	Obosilu	CO	01291	Y	

[7] https://gengo.ai/articles/what-is-ai-training-data/

2. **Algorithms/Models.** Many types of machine learning algorithms exist. **Algorithms** use "**training data**" to allow an AI assistant to train themselves to accomplish a specific task (more on that below)[7]. A **model** is what results once an algorithm is trained using data. Once trained, an AI Assistant can apply a model to new data.



Algorithm **Training data Set** **Model**

Example: Nonprofit ABC takes the dataset of contacts asked to donate at last year's bike-a-thon and trains an AI assistant using a machine learning algorithm to predict whether a particular contact is likely to donate, and then uses the resulting model to identify the most likely donors among a list of potential donors. Nonprofit ABC then provides each of its fundraisers for this year's bike-a-thon with an AI Assistant that uses that model to help the fundraiser identify who among their existing contacts is a likely donor for this year's bike-a-thon.

3. Tools/Infrastructure. Machine learning programming is now largely done using widely available open source tools (such as SparkML, PythonML, R, TensorFlow, and PyTorch). These **tools** allow an AI developer to use machine learning to train an AI assistant using a nonprofit's data to be capable of accomplishing a wide variety of tasks such as prediction, classification, or clustering (more on that below).

Source: https://www.learnbigdatatools.com/big-data-cross-infrastructure-and-api-landscape-2019/

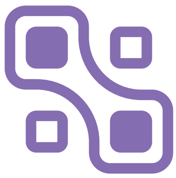
4. Computing Power. Not generally an issue for nonprofits, but more complex types of machine learning (including reinforcement learning or the creation of neural nets that use "hidden layers") may run up against the modern limits of computing power.

Machine Learning Tasks: What Can Machine Learning Do?

With the right data, model, tools, and computing power, machine learning can perform the following tasks (among many others): (1) classification; (2) prediction; (3) clustering; or (4) identification of key features.[8]

Classification

Prediction

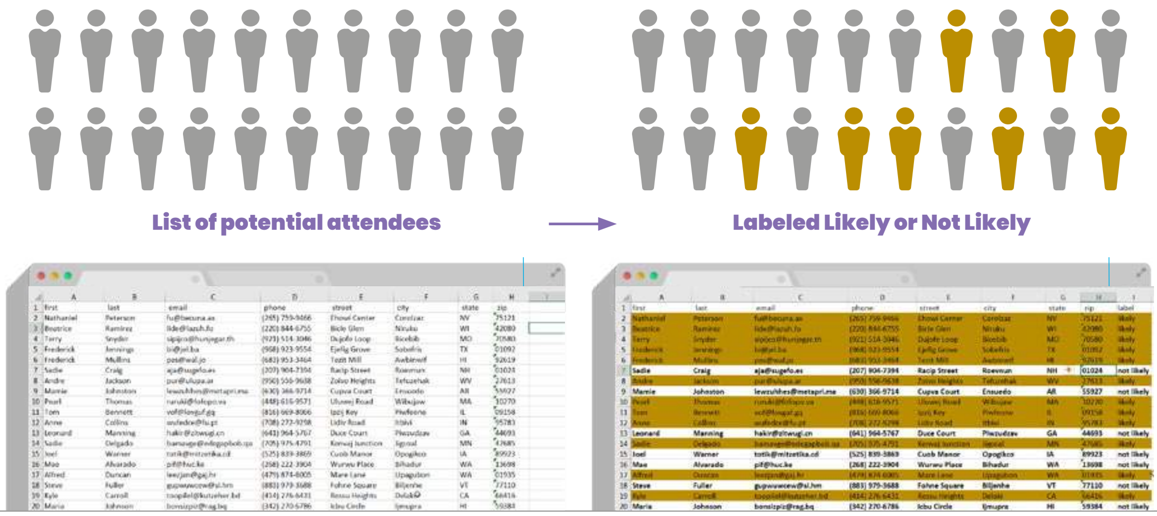


Clustering

Identification of key features

1. Classification. Using machine learning, an AI assistant can be trained to predict what label should be applied to a particular observation. In other words, an AI assistant can predict (classify) whether a record belongs in one category versus another category.

Example: Nonprofit XYZ is gearing up for its biggest fundraising event of the year: the Annual XYZ Gala. Nonprofit XYZ could use an AI Assistant to classify individuals into likely attendees vs. unlikely attendees.

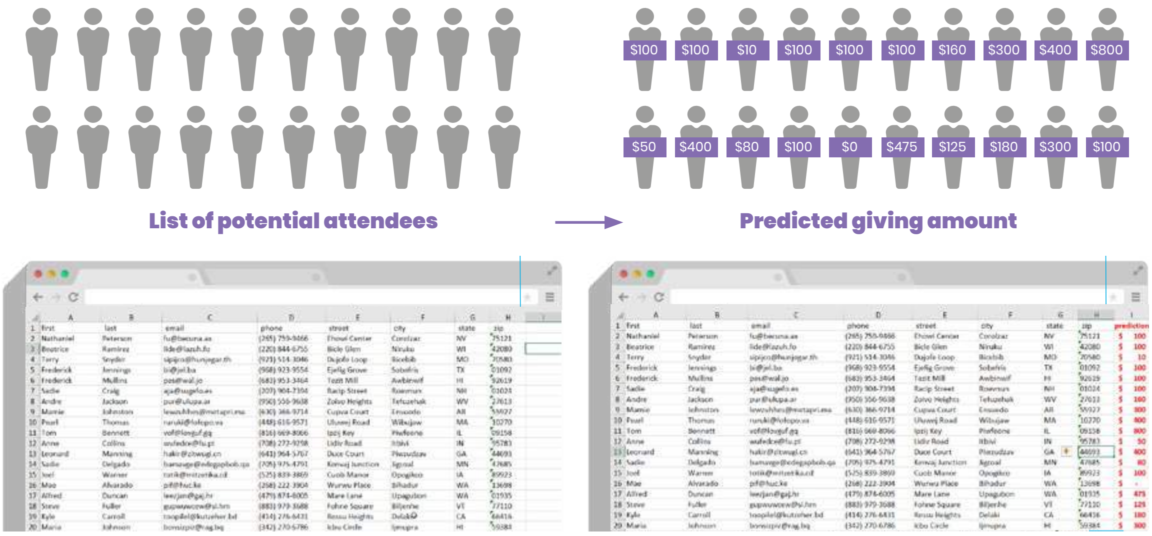


[8] https://hackernoon.com/choosing-the-right-machine-learning-algorithm-68126944ce1f

The accuracy of a classification model depends on the algorithm chosen, the availability of labeled training data, and how well the model is trained on the data. [9]

2. Prediction. An AI assistant can also be trained to predict a value you want to know based on the data you provide.

Example: For the Annual XYZ Gala, Nonprofit XYZ could also use an AI Assistant to predict how much each gala attendee will spend on the gala auction (the target value) based on information (features) for each attendee such as amount spent at previous gala auctions, age, number of years of attendance, and estimated net worth.



A predicted value could be continuous (like dollars spent at an auction) or discrete (like the number of auction items received). As with classification, the accuracy of a prediction model depends on the algorithm used, how effectively the model is trained, and the quality of the training data. This type of learning is often referred to as "regression learning".

[9] https://medium.com/machine-learning-for-humans/supervised-learning-2-5c1c23f3560d

3. Clustering. Machine learning allows an AI assistant to take unlabeled data and divide it into **clusters** of similar observations. Given a set of observations, an AI assistant can place each observation into a group of similar observations so the groups are distinct from each other. An AI assistant can then perform further analysis on each cluster to provide insights and/or make predictions.

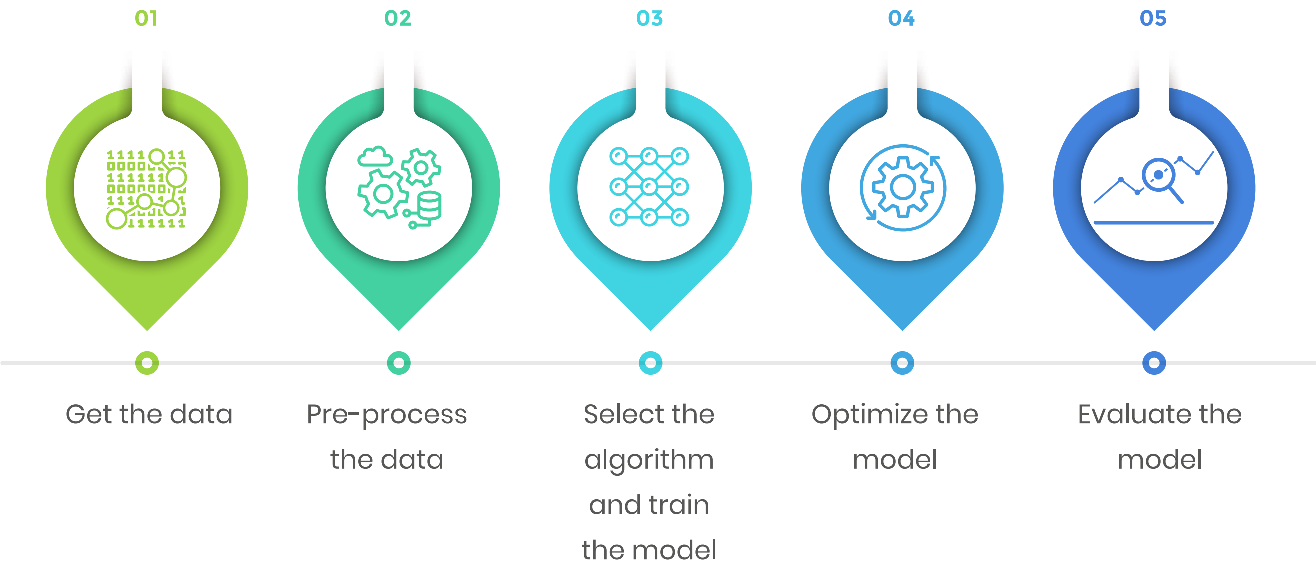
Example: Nonprofit XYZ has a dataset of last year's Annual XYZ Gala attendees and wants to cluster those attendees into distinct groups to better understand who attended the gala. An AI assistant could perform that clustering and tell Nonprofit XYZ that there are four distinct types of gala attendees that comprise the majority of attendees. Nonprofit XYZ then performs additional analyses to learn more about each cluster of attendees.

4. Identification of key features. In machine learning, this is often called "dimensionality reduction" or "feature selection." In plain English, this means to identify what features in the dataset are important to a particular machine learning model.

Example: Nonprofit XYZ's dataset of last year's Annual XYZ Gala attendees (and those invited who did not attend) has been enriched so that the dataset now contains hundreds of attributes for each individual. Using further analysis, nonprofit XYZ learns that the AI assistant's model relies on only five attributes for 97% of its analysis. This gives nonprofit XYZ insight into what attributes are the most important in predicting the likelihood of attendance, as well as allowing the nonprofit XYZ to be more efficient and effective in using its AI assistant.

Machine Learning Steps: How Does Machine Learning Work?

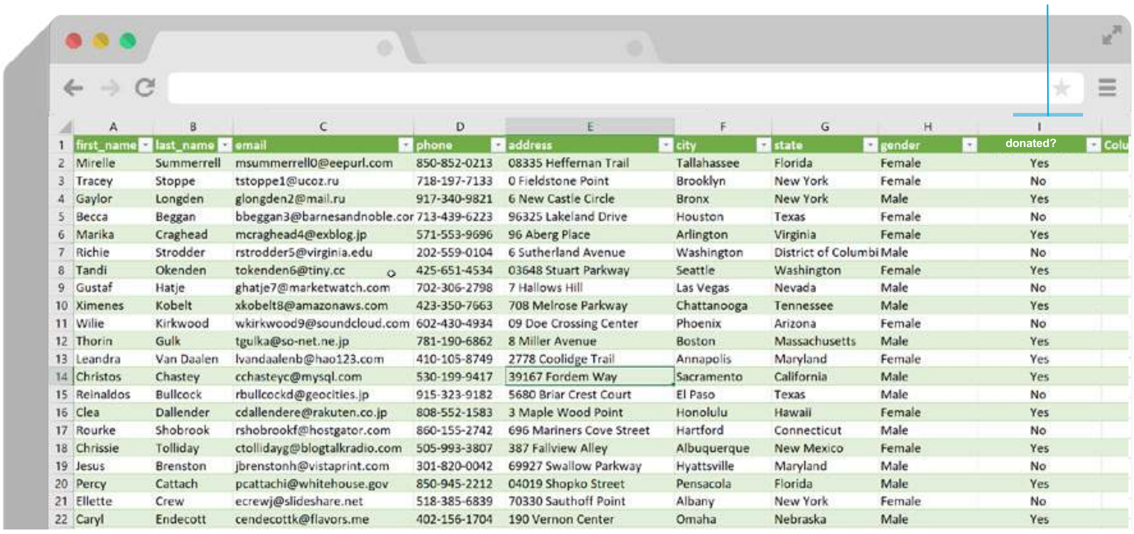
Training an AI assistant using machine learning requires several distinct steps: (1) obtain the training data; (2) pre-process the training data; (3) select the algorithm and train the model; (4) optimize the model; (5) evaluate the model. [10]



1. Obtain the training data. The first and often most important step involves the training data. If you want to train a model to perform classification or prediction, the training data must be labeled with the label or target value you want to predict. (If you want to predict what future fundraisers will raise, you need data with labels showing what past fundraisers did raise.)

> *Example: Nonprofit MNO wants to provide an AI assistant to its board of trustees to assist board members in meeting their annual "give or get" requirement of $5,000. So, the AI assistant gathers data from previous MNO fundraising campaigns that consists of 1,000 records of individuals asked to donate by board members, and whether or not the individuals actually donated (the label).*

[10] For an excellent course of practical machine learning, which provided the below methodology, see https://www.udemy.com/machinelearning/learn/v4/overview.

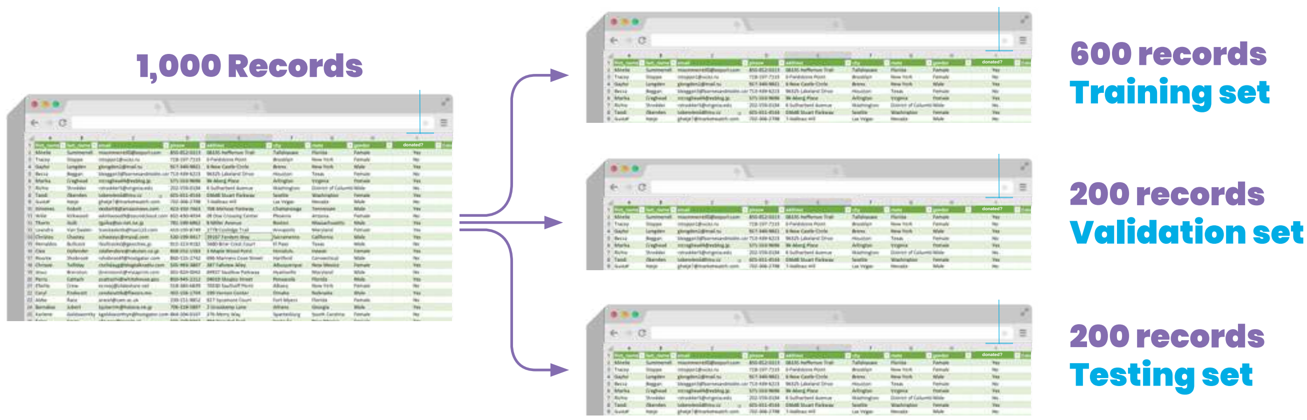


	first_name	last_name	email	phone	address	city	state	gender	donated?	Colu
2	Mirelle	Summerrell	msummerrell0@eepurl.com	850-852-0213	08335 Heffernan Trail	Tallahassee	Florida	Female	Yes	
3	Tracey	Stoppe	tstoppe1@ucoz.ru	718-197-7133	0 Fieldstone Point	Brooklyn	New York	Female	No	
4	Gaylor	Longden	glongden2@mail.ru	917-340-9821	6 New Castle Circle	Bronx	New York	Male	Yes	
5	Becca	Beggan	bbeggan3@barnesandnoble.cor	713-439-6223	96325 Lakeland Drive	Houston	Texas	Female	No	
6	Marika	Craghead	mcraghead4@exblog.jp	571-553-9696	96 Aberg Place	Arlington	Virginia	Female	Yes	
7	Richie	Strodder	rstrodder5@virginia.edu	202-559-0104	6 Sutherland Avenue	Washington	District of Columbi	Male	No	
8	Tandi	Okenden	tokenden6@tiny.cc	425-651-4534	03648 Stuart Parkway	Seattle	Washington	Female	Yes	
9	Gustaf	Hatje	ghatje7@marketwatch.com	702-306-2798	7 Hallows Hill	Las Vegas	Nevada	Male	No	
10	Ximenes	Kobelt	xkobelt8@amazonaws.com	423-350-7663	708 Melrose Parkway	Chattanooga	Tennessee	Male	Yes	
11	Wilie	Kirkwood	wkirkwood9@soundcloud.com	602-430-4934	09 Doe Crossing Center	Phoenix	Arizona	Female	No	
12	Thorin	Gulk	tgulka@so-net.ne.jp	781-190-6862	8 Miller Avenue	Boston	Massachusetts	Male	Yes	
13	Leandra	Van Daalen	lvandaalenb@hao123.com	410-105-8749	2778 Coolidge Trail	Annapolis	Maryland	Female	Yes	
14	Christos	Chastey	cchasteyc@mysql.com	530-199-9417	39167 Fordem Way	Sacramento	California	Male	Yes	
15	Reinaldos	Bullcock	rbullcockd@geocities.jp	915-323-9182	5680 Briar Crest Court	El Paso	Texas	Male	No	
16	Clea	Dallender	cdallendere@rakuten.co.jp	808-552-1583	3 Maple Wood Point	Honolulu	Hawaii	Female	Yes	
17	Rourke	Shobrook	rshobrookf@hostgator.com	860-155-2742	696 Mariners Cove Street	Hartford	Connecticut	Male	No	
18	Chrissie	Tolliday	ctollidayg@blogtalkradio.com	505-993-3807	387 Fallview Alley	Albuquerque	New Mexico	Female	Yes	
19	Jesus	Brenston	jbrenstonh@vistaprint.com	301-820-0042	69927 Swallow Parkway	Hyattsville	Maryland	Male	No	
20	Percy	Cattach	pcattachi@whitehouse.gov	850-945-2212	04019 Shopko Street	Pensacola	Florida	Male	Yes	
21	Ellette	Crew	ecrewj@slideshare.net	518-385-6839	70330 Sauthoff Point	Albany	New York	Female	No	
22	Caryl	Endecott	cendecottk@flavors.me	402-156-1704	190 Vernon Center	Omaha	Nebraska	Male	Yes	

1,000 Records

2. Pre-process the training data. Once you have a (labeled) data set, you import the data set so that your AI assistant can work with it. Once imported, you address redundant or missing data (e.g. birthday, employer, capacity). You then identify what you want your AI assistant to predict (the label or target value) and what you want your AI assistant to use to make the prediction (the dependent attributes/features). You then have your AI assistant split the data set into training, validation, and test sets of data. The **training set** consists of the records used by the AI assistant to learn the desired model. The **validation set** consists of the records used by the AI assistant to optimize the model. The **testing set** consists of the records used to assess how well the fully-optimized model performs. [11]

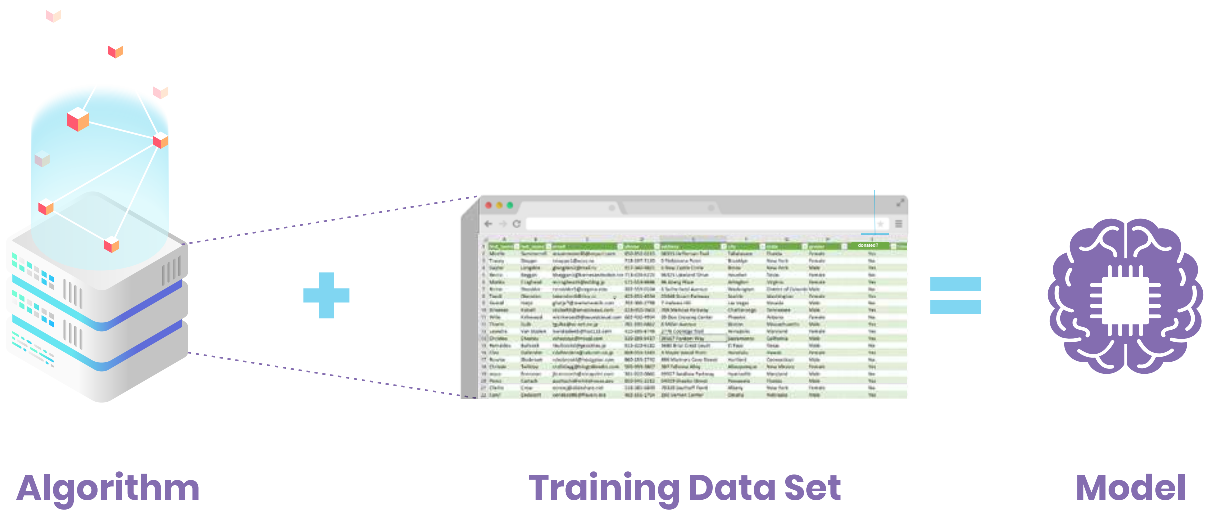
Example: Nonprofit MNO takes 1,000 records of high net worth individuals asked to donate by board members and selects 600 records for training, 200 for validation, and 200 records for testing. This procedure, if successful, will result in a model that Nonprofit MNO will have confidence in with regards to how well it will perform with predicting individuals that the AI assistant has never 'seen'. However, this process does not provide a guarantee of the model's validity. This results only after a model is put into practice and evaluated.



[11] https://machinelearningmastery.com/difference-test-validation-datasets/

3. **Select the algorithm and train the model.** Once the training data has been pre-processed, you select the machine learning algorithm appropriate to the task you want to be performed (classification, prediction, clustering, etc.). You then use the appropriate tool/infrastructure to train your AI assistant to perform the selected task (classify, predict, cluster, etc.) using the selected algorithm and the training set of data to develop a model that can perform the same task when applied to new data. This is also called "fitting the model to the training data set."

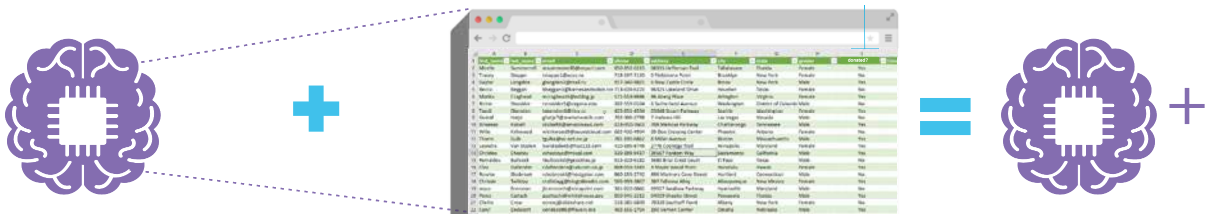
   Example: Nonprofit MNO selects a classification algorithm and uses the 600 records from the training set to train an AI assistant to classify each record as "likely to donate" or "not likely to donate".



4. **Optimize the model.** Using the validation set, the AI assistant can optimize the model developed from the training set. Every machine learning algorithm has "hyperparameters" that dictate how the algorithm works. Think of hyperparameters like settings on a blender. Depending on what you want to be blended, you select a different setting. Determining the optimal set of hyperparameters for a particular application is called "optimizing the hyperparameters", and is a critical step in improving the accuracy and reliability of a machine learning model.

   Example: Nonprofit MNO uses the records in the validation set to further tune the classification model the AI assistant learned. In this case, the ability to predict whether a particular individual was likely or not to donate when asked by a board member.

[12] A survey of machine learning algorithms is beyond the scope of this article. A good primer can be found here: https://medium.com/machine-learning-for-humans/supervised-learning-740383a2feab.

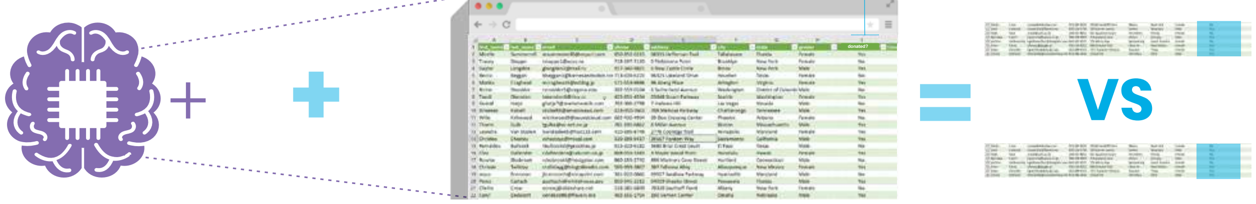


Model **Validation Data Set** **Optimized Model**

5. Evaluate the model. Finally, the AI assistants takes the optimized model and makes predictions using the designated test data that the machine has never 'seen'. Due to the fact that the actual target values or labels are known for the test data, the accuracy of the model can be determined by comparing those values against the predicted values. [13]

Example: Now that the AI assistant learned a model through the training and validation steps, it can be used to predict which of the 200 records in the test set are most likely to donate to Nonprofit MNO. The predictions that the AI assistant makes for the 200 test records are then evaluated, and a set of performance statistics are computed. These statistics measure how reliable the AI assistant can be expected to be when deployed to evaluate new records for Nonprofit MNO.

Predicted Result



Optimized Model **Testing Data Set** **Actual result**

[13] There are many metrics used to evaluate machine learning models, specific to the types of algorithm being used. https://towardsdatascience.com/metrics-to-evaluate-your-machine-learning-algorithm-f10ba6e38234 and https://medium.com/usf-msds/choosing-the-right-metric-for-machine-learning-models-part-1-a99d7d7414e4 and https://medium.com/usf-msds/choosing-the-right-metric-for-evaluating-machine-learning-models-part-2-86d5649a5428

Final Thoughts: When is AI, AI?

“AI” seems to be everywhere. However, "AI" means different things to different people. Just seeing the term "AI" doesn’t necessarily tell you what the tool does and how it does it. Even more challenging is that the results of AI and non-AI tools often initially appear similar or even identical. You can’t tell something is “AI” by looking at it or even its results.

So how can you tell something is AI?

Any software that uses data, algorithms/model, tools/infrastructure and computer power (machine learning requirements) to perform classification, prediction, clustering, or identification of key features (machine learning tasks) using a process of obtaining data, preprocessing data, selecting algorithms and training models, optimizing parameters, and evaluating models (machine learning steps) is applying a subclass of artificial intelligence that some people prefer to call machine intelligence or machine learning.

In general, data scientists use many tools ranging from data cleaning, statistics, and complex algorithms. AI in practice currently consists of the utilization of many data science tools that are not necessarily considered machine learning. Ultimately, however, these techniques are meant to prepare data to be fed into a machine learning algorithm. This is what empowers the AI assistant to be able to make decisions about objects/people that it has never seen before. **This is when AI is AI.**

Even then, AI software can vary in how much it leverages machine learning.

An AI assistant might be trained once using a generic data set and a selected algorithm, resulting in a model that is never again optimized, and that model is used for all future predictions without further machine learning.

Compare that to an AI assistant that is constantly retrained on new data sets using algorithms selected for effectiveness with particular data sets, with each resulting model re-optimized, and a feedback loop created such that the models are constantly improved by further machine learning based on real-world performance of each model.

Both are “AI”, but are quite different in capabilities and capacity for improvement.

> *Example: software may be powered by an AI assistant that is generically trained to recognize a likely fundraiser or it may be powered by an AI assistant that is specifically trained to recognize a likely fundraiser for Nonprofit JKL and their particular types of fundraising campaigns, with a feedback loop to improve the AI assistant’s performance over time with regards to Nonprofit JKL’s specific campaigns.*

The Bottom Line

AI tools for nonprofits will proliferate and rapidly advance in the coming months and years. As with all new technology, AI will be best leveraged by educated consumers who ask the right questions and are able to understand the answers they receive. To that end, we have included a list of questions that nonprofits professionals can ask AI service providers to better understand the tools today that will continue to transform the landscape of donor development tomorrow.

Appendix: Questions Nonprofits Should Ask AI Service Providers

1. **Data**
   a. What data sets does your machine learning rely on?
   b. How many observations are required to train your machine learning tool?
   c. How many and what attributes are you using to train your machine learning tool?
   d. How do you deal with missing features in the dataset?
   e. How are you splitting the dataset for training, validation, and testing?
2. **Algorithms/Model**
   a. What machine learning tasks are your tools performing?
   b. How do those machine learning tasks support what the software does?
   c. What machine learning algorithm/model did you select to accomplish those tasks?
   d. Why did you select that particular algorithm/model?
   e. How are you optimizing the model?
   f. What metrics are you using to evaluate the predicted values versus the test values?
   g. How did the model perform on those metrics?
   h. How are the algorithms and models selected, trained, and optimized?
      i. Is the same algorithm used for every organization or are different algorithms selected for different organizations in order to create models?
      ii. Is the model trained once or is it retrained for every organization?
      iii. Is the model optimized once or is it re-optimized for every organization?
   i. Is there a feedback process to continuously improve the model(s)?
3. **Tools/Infrastructure**
   a. What software tools are you using to train the machine learning model?
   b. Why did you select that particular software?
4. **Computer power/Security/Privacy**
   a. Do you share my datasets used for training the AI with third parties?
   b. Are you duplicating/storing copies of data even after the original data sets are deleted?
   c. Where are you storing the trained models?
   d. Where are you storing the results of the training?
   e. How is the above secured?
   f. Do you share the above information with any third parties?

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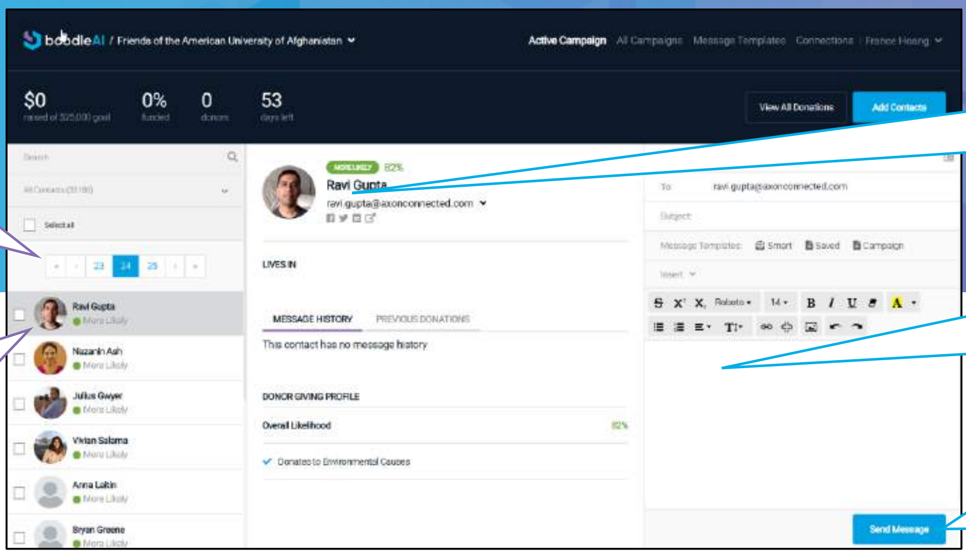
1. Your supporters choose what contact lists they securely connect to boodleAI.

2. boodle identifies the contacts in your network that you should engage for contributions.



3. Your supporters select who to contact. Their contacts are never shared with third parties or the nonprofit itself.

4. boodle provides recommended messages, reducing the effort required by supporters to make an ask for contributions.

5. Messages are sent from your supporters' personal email to their peers – the most effective ask.

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- ✓ Email open rates >80%
- ✓ Email donation rates 100x the average for nonprofits

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