

WEB-RADR WP2A

Report on Language Classifiers

Type of document:	Report
Version:	1.0
Date:	30 September 2017
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Introduction

WEB-RADR's Work Package 2A has been dedicated to conducting social media monitoring activities for pharmacovigilance purposes. The outputs of these activities have been analyzed and evaluated by Work Packages 2B and 4, with findings summarized in reports from those work packages. WP2A additionally was tasked with developing adverse event classifiers for French- and Spanish-language social media data, as part of the effort to adapt Epidemico's MedWatcher Social platform for the European context.

MedWatcher Social is a social media monitoring platform that collects publicly available data from Internet social media sources. MedWatcher Social is designed to complement existing safety efforts by supporting post-marketing safety surveillance. Filtering and classification algorithms are applied to identify content relating to adverse event experiences with medical products (namely drugs, devices, and vaccines). The filtered, de-identified, and aggregated data are then made available to end users for review and analysis via an interactive Web-based visualization dashboard.

This document provides an overview of the process for developing the French and Spanish classifiers, as well as an overview of the data in the languages that has been collected and classified via the MedWatcher Social system to date.

Language Identification

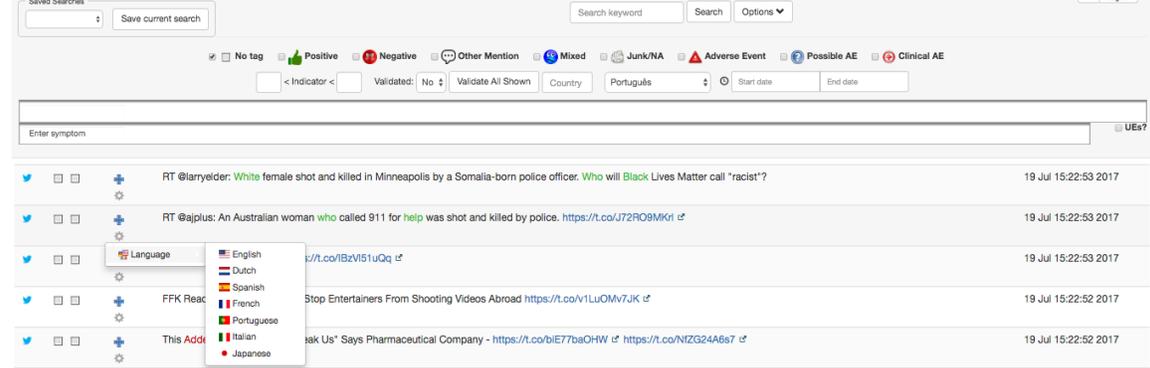
As two separate French and Spanish classifiers would be developed and implemented separate from the existing English classifier, it was necessary to create a mechanism for identifying the language in any given post in order to then automatically determine which classifier should be used for that post. While language identification can be achieved by creating additional classifiers, we chose a hybrid automatic-manual approach in order to leverage existing language metadata that often accompanies each post.

Manual Tagging

One drawback to using metadata to identify post language is that it may not always be available. Metadata includes any other piece of information that might be available aside from the post text, such as timestamp, source references and demographic information about the post author. The availability of this information can vary greatly among different sources or depend on individual users' settings. In addition, it may not always be accurate or up-to-date. For example, if metadata may be generated based on a user's profile, it may not always completely represent the post that it accompanies. This is particularly true when attempting to use location information to determine language; for example, a user may be based in Spain but chooses to participate in English-language forums.

We identified language based on language tags wherever possible. We then used the curation platform to manually annotate or correct falsely identified languages.

Tagging language in the curation platform



The screenshot displays the WEB-RADR curation platform interface. At the top, there is a search bar with a "Search keyword" field and a "Search" button. Below the search bar, there are several filter options: "No tag", "Positive", "Negative", "Other Mention", "Mixed", "Junk/NA", "Adverse Event", "Possible AE", and "Clinical AE". There are also fields for "Indicator", "Validated", "Validate All Shown", "Country", "Portugals", "Start date", and "End date". A "Saved Searches" dropdown menu is visible on the left. The main content area shows a list of tweets. A dropdown menu is open over the first tweet, showing language options: English, Dutch, Spanish, French, Portuguese, Italian, and Japanese. The tweets listed include: "RT @larryelder: White female shot and killed in Minneapolis by a Somalia-born police officer. Who will Black Lives Matter call 'racist'?", "RT @ajplus: An Australian woman who called 911 for help was shot and killed by police. https://t.co/J72R09MKri", "https://t.co/IBzV151uQq", "FFK React Stop Entertainers From Shooting Videos Abroad https://t.co/v1LuDMv7JK", and "This Adde ask Us" Says Pharmaceutical Company - https://t.co/biE77baOHw https://t.co/NIZG24A6s7".

Once the language has been determined for a post, that post is then routed to the appropriate language collection, with each language having its own data collection. Separating the posts into different language collection also reduces complications in managing and implementing product, symptom and PII taxonomies that may be developed specifically for each language.

Classifier Development

Based off of Epidemico's previous work in automated adverse event classification, two additional three-class multinomial naïve Bayes classifiers were developed – one for French-language posts and one for Spanish-language posts. The classifiers have been trained to recognize traits of text that describe potential adverse events in their respective languages and characterizes incoming data as one of three classes – Proto-AE, Mention, or Junk – based on how previous posts were categorized by human curators in a training set. This processing is accomplished with three steps: (1) word bigram tokenization, (2) count-based vectorization, and (3) Multinomial Naive Bayes classification. By tagging Mentions in addition to Proto-AEs and Junk (i.e., ternary classification), the classifiers provide expanded modeling power than other types that implement binary classification, resulting in higher predictive performance as well as better interpretability.

Development of Training Sets

Two distinct training sets consisting of French- and Spanish-language social media posts were created to train each language classifier, essentially teaching the classifier how to recognize incoming data as potential adverse drug reactions and assign classifications appropriately. Spanish and French social media posts were hand-tagged by human curators that are either proficient in or native speakers of each language. Curators were assigned to review either the Spanish data collection or the French data collection and instructed to select a tag for each post. Posts that contained language describing a potential adverse drug reaction were tagged as a Proto-AE. Additionally, curators were instructed to tag any posts without descriptions of adverse events as Mentions, and posts without reference to actual medical products as Junk (e.g., false positives for drug names, such as other products or people with identical names). As of

September 2017, the Spanish training set contains 7,313 posts, while the French training set contains 2,182 posts.

Curation platform and tags

	Despues de 2 nicotil y 2 zaldiar no se me quita el puto dolor de cabeza :))))))	22 Jun 09:29:43 2016
	Un cuarto lleno de coreanos, brasileños, taiwaneses y tailandeses hablando al mismo tiempo 😂 Ni el Zaldiar me quita este dolor de cabeza.	21 Jun 23:54:01 2016
	Es el segundo diclofenac que me tomo en el día y no se me pasa el dolor de cabeza 😞	19 Jun 22:42:52 2016
	Todas las noches antes de dormir me tomo un diclofenac . Es más adictivo que las drogas eso.	18 Jun 22:32:19 2016

Sample posts and curation protocol

Es el **segundo diclofenac** que me tomo en el día y no se me pasa el dolor de cabeza 😞

Post would be tagged as a Proto-AE. The phrase, “no se me pasa el dolor de cabeza,” would be added to the Spanish symptom dictionary as a synonym for Drug ineffective MedDRA PT.

Certes ce **Zomig** ne m'a pas donné de **palpitations** pour une fois. Mais il ne fait pas non plus du tout effet. #vdm #migraine

Post would be tagged as a Proto-AE. The phrase, “palpitations,” would be added to the French symptom dictionary as a synonym for Palpitations MedDRA PT.

Taxonomy Development

Given the high degree of overlap in product trade names in different countries, a separate product taxonomy was not developed for each language; rather, the existing product taxonomy was leveraged since it already contained international trade names.

Two language-specific symptom dictionaries were created to enable the automatic coding of colloquial phrases describing ADRs into MedDRA terminology, using natural language processing. Using the existing English language symptom taxonomy as a basis, we created a spreadsheet containing 2,000 of the MedDRA Preferred Terms most commonly mentioned in social media. The curators then added French and Spanish colloquial phrases to the most appropriate Preferred Term based on social media posts reviewed during the curation process or based on their own familiarity with the language. MedDRA Lower level terms were also initially added as synonyms to provide an expedient starting point for taxonomy development.

French Symptom Taxonomy

lft_french	pt_french	synonyms_french	lft_num
Absence d'effet medicamenteux	Inefficacite medicamenteuse	je me sens toujours aussi vide, absence d'effet medicamenteux, aucun bénéfice, rien n y fait, il marche pas, ne fait plus effet, ça m'fais plus, mm pas il fait effet	10023610

As of September 2017, the French symptom dictionary contained 782 synonyms mapping to 690 MedDRA Preferred Terms. The Spanish symptom dictionary contained 1010 synonyms mapping to 717 MedDRA Preferred Terms.

Data Collection and Classification

As of September 2017, the Spanish data collection contained 10,721,608 posts. A total of 823,141 posts from this collection have been tagged as Proto-AEs (8% of all Spanish posts). The French data collection contains 3.32 million posts, and 98,820 of these have been automatically tagged as Proto-AEs (3% of all French posts). The majority of these posts (85%) were collected from Twitter. The most frequently reported Preferred Term among the Spanish data was *Altered state of consciousness*. The most frequently reported Preferred Term among the French data was been *Drug ineffective*.

The performance of the Spanish classifier differed from that of the French classifier; performance on the three different post types also varied. The highest rate of precision was seen among Spanish Junk posts (0.97), whereas the highest rate of recall was seen among Spanish Proto-AE posts (0.89). In sum, the Spanish classifier had a precision of 0.89 and recall of 0.83; the French classifier had 0.77 precision and 0.76 recall.

Multinomial Bayesian Classifier Performance

Precision is the fraction of retrieved instances that are relevant. Recall is the fraction of relevant instances that are retrieved. F1 score is the harmonic mean of precision and recall

SPANISH			
Post Type	Precision	Recall	F1 Score
Junk	0.97	0.74	0.84
Proto-AE	0.48	0.89	0.62
Mention (non-AE)	0.96	0.84	0.90
Avg/Total	0.89	0.83	0.85
FRENCH			
Post Type	Precision	Recall	F1 Score
Junk	0.84	0.69	0.76
Proto-AE	0.51	0.60	0.55
Mention (non-AE)	0.78	0.83	0.81
Avg/Total	0.77	0.76	0.76

Discussion

Sample datasets containing 1,000 random French- and Spanish-language posts were reviewed by a native French speaker and a native Spanish speaker (authors PT and

TM) after the data had been processed by the automated classifier. This section summarizes qualitative observations resulting from this review.

Generally, there were fewer true positives among the French and Spanish data than among the English data; among true positives. Within the French dataset, only 1% of Proto-AEs were true positives. There was less variety in reported symptoms, as well; for example, no correspondence was found when comparing the Spanish sample dataset to a list of the most frequently report ADRS from a regulatory database.

Most of the posts in the Spanish dataset were geolocated to countries in South America or Central America, which may have biased the sample. Many of these were tweets in which a user was indicating a need or a request for a medical product in scarcity. This type of post content would presumably be much less prevalence in tweets from European users (specifically, Spain). For the French posts with geolocation information, most users were based in France, followed by Brussels and Canada. No location-based patterns were apparent among the French posts.

Product indications appeared quite frequently among both French and Spanish posts, resulting in medical conditions or reason for product administration to be falsely identified as a symptom of an adverse drug reaction, and underscoring the importance of incorporating product indications into automated adverse event classifiers.

The cause of the relatively small outputs remains unclear and may have been due to one or several reasons. First, it's possible that the data sources used for WEB-RADR were not as appropriate for French and Spanish. As data collection for these languages did not start when the consortium had access to Facebook data, it's possible that that platform would have provided more relevant data in these languages specifically, due to Facebook's global use. Second, the small number of social media ADRs may be indicative of cultural differences regarding online medical discussions among French and Spanish speakers. Third, the training sets and taxonomies are still being developed for Spanish and French languages and are relatively small compared to the English training sets and taxonomies, potentially posing a technology limitation. Lastly, it should be noted that English is often used universally in many online forums dedicated to discussing medical conditions; therefore, a user who may ordinarily post on social media in Spanish, for instance, may choose to write English posts in other settings. An in-depth research study investigating the behavior of Spanish and French social media users may provide more insights into the feasibility of monitoring ADRs in various languages in social media.

There are many words used frequently in both the medical and non-medical settings that can pose particularly challenges to automated classifiers and trigger false positives – in any language. Words that describe being in pain, feeling sick, vomiting, sleeping, even dying are common phrases that are often presented colloquially for emphasis in hyperbolic yet casual statements; for example, a user may say, “I think I’m going to die,” to underscore how terrible she feels, even when it is certain that she is likely not going to perish in that instant. Additionally, nuanced tones can pose challenges to automated classifiers; for example, sarcasm can be difficult for even humans to identify in written text. As such, it is important for training sets in any language to comprise a wide range of tones in order to inform the classifier with a breadth of examples.

Certain types of words proved problematic for Spanish automated classification specifically. Abbreviations, first names and place names, or email addresses were often falsely identified as drug names. For instance, a large number of tweets mentioned “tobi”, intended in this context as a nickname for Tobias, but identified and tagged as a trade name for tobramycin. Additionally, the word “vibra” had been identified as a trade name for doxycycline, was frequently tagged due to its significance as a Spanish verb. This could indicate a need for a language-specific product taxonomy and a language-specific PII dictionary. It may also suggest that certain trade names may be less suitable for digital listening due to their likeliness to appear frequently in other contexts not related to drug safety. This challenge could be mitigated by implementing a strategy such as the NERd-Twitter algorithm, developed by Uppsala Monitoring Centre to eliminate ambiguous search terms, and could be applied in each language context to determine which terms should be used for each collection.¹

Another factor to consider is the need to accommodate for special characters such as accents. Prior to classification, accents, punctuation, and other special characters are often removed from the post text to facilitate processing; or, special characters can render differently in programs like Excel. If not handled correctly, these characters can cause breaks in text that cause words to be falsely tagged as drug names.

¹ Hedfors S, et al. Search term reduction analysis on Reddit data – Epidemico and Uppsala Monitoring Centre joint subproject in WEB-RADR WP2B

Appendix A

WEB-RADR Product Search Terms

Product Name	Active Ingredients / Generics	Search Terms
acarbose	acarbose	acarbose
Aclasta	zoledronic acid	Aclasta
Adalat	nifedipine	Adalat
Adefin	nifedipine	Adefin
Afinitor	everolimus	Afinitor
aldesleukin	aldesleukin	aldesleukin
alemtuzumab	alemtuzumab	alemtuzumab
aliskiren	aliskiren	aliskiren
Allurene	dienogest	Allurene
Alpharadin	radium Ra 223 dichloride	Alpharadin
amlodipine and valsartan	amlodipine,valsartan	amlodipine and valsartan
amlodipine-benazepril	amlodipine,benazepril	amlodipine and benazepril
amlodipine, valsartan and hydrochlorothiazide	amlodipine,valsartan,hydrochlorothiazide	amlodipine valsartan hydrochlorothiazide
Anafranil	clomipramine	Anafranil
Anastrozol	anastrozole	Anastrozol
anastrozole	anastrozole	anastrozole
Apidra	insulin glulisine	Apidra
Aranesp	darbepoetin alfa	Aranesp
Arcapta/Onbrez	Indacaterol Maleate	Onbrez, Arcapta
Aredia	pamidronate	Aredia
Arimidex	anastrozole	Arimidex
artemether and lumefantrine	artemether,lumefantrine	lumefantrine
AscoTop	zolmitriptan	AscoTop
Atenolol	atenolol	Atenolol
Aubagio	teriflunomide	Aubagio
Avlocardyl	propranolol	Avlocardyl
Axanum	esomeprazole,acetylsalicylic acid	Axanum

Baclofen	Baclofen	Baclofen
basiliximab	basiliximab	basiliximab
Betaferon	interferon beta-1b	Betaferon
Betaseron	interferon beta-1b	Betaseron
Betazide	metoprolol tartrate	Betazide
bicalutamide	bicalutamide	bicalutamide
Brilinta	Ticagrelor	Brilinta
Brilique	Ticagrelor	Brilique
budesonide	budesonide	budesonide
Budicort	budesonide	Budicort
Cabazitaxel	Cabazitaxel	Cabazitaxel
canakinumab	canakinumab	canakinumab
Caprelsa	vandetanib	Caprelsa
carbamazepine	carbamazepine	carbamazepine
Cardioxane	dexrazoxane	Cardioxane
Casodex	bicalutamide	Casodex
Ceftaroline foramil	Ceftaroline foramil	Ceftaroline
ceritinib	ceritinib	ceritinib
Certican	everolimus	Certican
Chronadalat	nifedipine	Chronadalat
Chronadalate	nifedipine	Chronadalate
cinacalcet	cinacalcet	cinacalcet
Claritrast	iopromide	Claritrast
Clarograf	iopromide	Clarograf
Climagest	norethisterone,estradiol valerate	Climagest
Climaval	estradiol valerate	Climaval
Climesse	norethisterone,estradiol valerate	Climesse
clomipramine	clomipramine	clomipramine
clopidogrel	clopidogrel	clopidogrel
clozapine	clozapine	clozapine,clozapine

Clozaril	clozapine	Clozaril
Co-Diovan	valsartan,hydrochlorothiazide	Co Diovan, Cotareg
Compesk	interferon beta-1b	Compesk
Comtan	entacapone	Comtan
Cosentyx	secukinumab	Cosentyx
Cosudex	bicalutamide	Cosudex
cyclosporin	cyclosporin	cyclosporin
darbepoetin alfa	darbepoetin alfa	darbepoetin
deferasirox	deferasirox	deferasirox
deferoxamine	deferoxamine	deferoxamine
Denosumab	Denosumab	Denosumab
Desferal	deferoxamine	Desferal, Desferin
dexrazoxane	dexrazoxane	dexrazoxane
Diclofenac	diclofenac	diclofenac
dienogest	dienogest	dienogest
Diovan	valsartan	Diovan, Tareg
Diprivan	propofol	Diprivan
Dociton	propranolol	Dociton
dronedarone	dronedarone	dronedarone
entacapone	entacapone	entacapone
Entresto	valsartan,sacubitril	Entresto
esomeprazole and acetylsalicylic acid	esomeprazole,acetylsalicylic acid	esomeprazole and acetylsalicylic acid
Estraderm	estradiol hemihydrate	Estraderm
Estradiol	estradiol	Estradiol
estradiol hemihydrate	estradiol hemihydrate	estradiol hemihydrate
estradiol valerate	estradiol valerate	estradiol valerate
ethinylestradiol and gestodene	ethinylestradiol,gestodene	ethinylestradiol and gestodene
Eucreas	vildagliptin,metformin	Eucreas
everolimus	everolimus	everolimus
Exelon	rivastigmine	Exelon

Exelon Patch	rivastigmine transdermal	exelon patch
Exforge	amlodipine,valsartan	Exforge
Exforge HCT	amlodipine,valsartan,hydrochlorothiazide	Exforge HCT
Exjade	deferasirox	Exjade
Extavia	interferon beta-1b	Extavia
famciclovir	famciclovir	famciclovir
Famvir	famciclovir	Famvir, Oravir
Fanapt	iloperidone	Fanapt
Farydak	panobinostat	Farydak
Fedra	ethinylestradiol,gestodene	Fedra
Feloday	felodipine	Feloday
Felodipin	felodipine	Felodipin
felodipine	felodipine	felodipine
Felodur	felodipine	Felodur
Femara	letrozole	Femara
Femiane	ethinylestradiol,gestodene	Femiane
Femodette	ethinylestradiol,gestodene	Femodette
Ferona	interferon beta-1b	Ferona
Ferro Gyn	ferrous glycine sulfate,folic acid	Ferro Gyn
Ferro Sanol	ferrous glycine sulfate	Ferro Sanol
Ferro Sanol Gyn	ferrous glycine sulfate,folic acid	Ferro Sanol Gyn
ferrous glycine sulfate	ferrous glycine sulfate	ferrous glycine
ferrous glycine sulfate and folic acid	ferrous glycine sulfate,folic acid	ferrous glycine sulfate and folic acid
filgrastim	filgrastim	filgrastim
fingolimod	fingolimod	fingolimod
Fluenz	influenza	Fluenz
FluMist	influenza	FluMist,flu spray
fluvastatin	fluvastatin	fluvastatin
Galvus	vildagliptin	Galvus
Gilenya	fingolimod	Gilenya

Gitsalat	nifedipine	Gitsalat
Glicobase	acarbose	Glicobase
Glivec	imatinib	Glivec
Glucobay	acarbose	Glucobay
Gluconase	acarbose	Gluconase
Glucor	acarbose	Glucor
Glumida	acarbose	Glumida
glycopyrronium bromide	glycopyrronium bromide	glycopyrronium
Gynera	ethinylestradiol,gestodene	Gynera
Gynovin	ethinylestradiol,gestodene	Gynovin, Gynoden
Ilaris	canakinumab	Ilaris
iloperidone	iloperidone	iloperidone
imatinib	imatinib	imatinib
Imodium Multi-Symptom	loperamide and simethicone	Imodium
indacaterol and glycopyrronium	Indacaterol Maleate, glycopyrronium bromide	indacaterol and glycopyrronium
Indacaterol Maleate	Indacaterol Maleate	Indacaterol
Inderal	propranolol	Inderal
Inderalici	propranolol	Inderalici
insulin glargine	insulin glargine	glargine
insulin glulisin	insulin glulisine	glulisine
interferon beta-1b	interferon beta-1b	interferon beta 1b
Invega	paliperidone	Invega
Invega Sustenna	paliperidone palmitate	Invega Sustenna
iopromide	iopromide	iopromide
Istubal	tamoxifen	Istubal
Jakavi	Ruxolitinib Phosphate	Jakavi
Jevtana	Cabazitaxel	Jevtana
Keppra	levetiracetam	Keppra
Kombiglyze	saxagliptin	Kombiglyze
Lamisil	terbinafine	Lamisil

Lantus	insulin glargine	Lantus
Lemtrada	alemtuzumab	Lemtrada
Lescol	fluvastatin	Lescol
letrozole	letrozole	letrozole
Levetiracetam	levetiracetam	Levetiracetam
Levitra	vardenafil hydrochloride	Levitra
levodopa/entacapone/carbidopa	levodopa,entacapone,carbidopa	levodopa entacapone carbidopa
Lioresal	Baclofen	Lioresal
lixisenatide	lixisenatide	lixisenatide
Lodene	ethinylestradiol,gestodene	Lodene
Logest	ethinylestradiol,gestodene	Logest
loperamide and simethicone	loperamide and simethicone	loperamide and simethicone
Lotrel	amlodipine,benazepril	Lotrel
Lucentis	ranibizumab	Lucentis
lumiracoxib	lumiracoxib	lumiracoxib
Lunafem	ethinylestradiol,gestodene	Lunafem
Lyxumia	lixisenatide	Lyxumia
Meliane	ethinylestradiol,gestodene	Meliane
Meloden	ethinylestradiol,gestodene	Meloden
methylphenidate	methylphenidate	methylphenidate
metoprolol tartrate	metoprolol tartrate	metoprolol
Mimpara	cinacalcet	Mimpara
Minigeste	ethinylestradiol,gestodene	Minigeste
Multaq	dronedarone	Multaq
mycophenolic acid	mycophenolic acid	mycophenolic acid
Myfortic	mycophenolic acid	Myfortic
naproxen and esomeprazole	naproxen,esomeprazole	naproxen and esomeprazole
Navoban	tropisetron	Navoban
Neoral	cyclosporin	Neoral
Neulasta	pegfilgrastim	Neulasta

Neupogen	filgrastim	Neupogen
Nexavar	sorafenib	Nexavar
nifedipine	nifedipine	nifedipine
Niferex	ferrous glycine sulfate	Niferex
nilotinib	nilotinib	nilotinib
Nitroderm	nitroglycerine	Nitroderm, Nitriderm
nitroglycerine	nitroglycerine	nitroglycerine
Nolvadex	tamoxifen	Nolvadex
norethisterone and estradiol valerate	norethisterone,estradiol valerate	norethisterone and estradiol valerate
Nplate	romplostim	Nplate
Obsidan Fe++	ferrous glycine sulfate	Obsidan
octreotide	octreotide	octreotide
omalizumab	omalizumab	omalizumab
Onglyza	saxagliptin	Onglyza
oxcarbazepine	oxcarbazepine	oxcarbazepine
paliperidone	paliperidone	paliperidone
paliperidone palmitate	paliperidone palmitate	paliperidone palmitate
pamidronate	pamidronate	pamidronate
panitumumab	panitumumab	panitumumab
panobinostat	panobinostat	panobinostat
pasireotide	pasireotide	pasireotide
pegfilgrastim	pegfilgrastim	pegfilgrastim
Perfudal	felodipine	Perfudal
Pertensal	nifedipine	Pertensal
pilocarpine	pilocarpine	pilocarpine
Plavix	clopidogrel	Plavix
Plendil	felodipine	Plendil, Flodil
Ponesta	zolmitriptan	Ponesta
Prandase	acarbose	Prandase
Precose	acarbose	precose

Preslow	felodipine	Preslow
Prevex	felodipine	Prevex
Prexige	lumiracoxib	Prexige
Proleukin	aldesleukin	Proleukin
Prolia	Denosumab	Prolia
propofol	propofol	propofol
Propranolol	propranolol	propranolol
Proscope	iopromide	Proscope
Pulmaxan	budesonide	Pulmaxan
Pulmicort	budesonide	pulmicort
radium Ra 223 dichloride	radium Ra 223 dichloride	radium dichloride,Ra 223
ranibizumab	ranibizumab	ranibizumab
Rasilez	aliskiren	Rasilez
Regorafenib	Regorafenib	Regorafenib
Remidex	anastrozole	Remidex
Riamet	artemether,lumefantrine	Riamet
Ritalin	methylphenidate	Ritalin
rivastigmine	rivastigmine	rivastigmine
rivastigmine transdermal	rivastigmine transdermal	rivastigmine transdermal
romplostim	romplostim	romplostim
Ruxolitinib Phosphate	Ruxolitinib Phosphate	Ruxolitinib
sacubitril and valsartan	valsartan,sacubitril	sacubitril and valsartan
Salagen	pilocarpine	Salagen
Sandimmun	cyclosporin	Sandimmun
Sandostatin	octreotide	Sandostatin, Sandostatine
saxagliptin	saxagliptin	saxagliptin
Sebivo	telbivudine	Sebivo
secukinumab	secukinumab	secukinumab
Seebri	glycopyrronium bromide	Seebri
Seloken	metoprolol tartrate	Seloken, Beloken

Selozok	metoprolol tartrate	Selozok
Signifor	pasireotide	Signifor
Simulect	basiliximab	Simulect
sorafenib	sorafenib	sorafenib
Spartofer	ferrous glycine sulfate	Spartofer
Spesicor	metoprolol tartrate	Spesicor
Spirocort	budesonide	Spirocort
Stabilic	acarbose	Stabilic
Stalevo	levodopa, entacapone, carbidopa	Stalevo
Staxyn	vardenafil hydrochloride	Staxyn
Stilnox	zolpidem	Stilnox
Stivar	Regorafenib	Stivar
Stivarga	Regorafenib	Stivarga
Sumial	propranolol	Sumial
Tactevo	influenza	Tactevo
tamoxifen	tamoxifen	tamoxifen
Tasigna	nilotinib	Tasigna
Tegretol	carbamazepine	Tegretol
Tekturna	aliskiren	Tekturna
telbivudine	telbivudine	telbivudine
Tenormin	atenolol	Tenormin, Tenormine
terbinafine	terbinafine	terbinafine
teriflunomide	teriflunomide	teriflunomide
Ticagrelor	Ticagrelor	Ticagrelor
Tobi	tobramycin	Tobi
tobramycin	tobramycin	tobramycin
Topamax	topiramate	Topamax
topiramate	topiramate	topiramate
Trileptal	oxcarbazepine	trileptal
tropisetron	tropisetron	tropisetron

Ultibro	Indacaterol Maleate, glycopyrronium bromide	Ultibro
Ultravist	iopromide	Ultravist
Valodex	tamoxifen	Valodex
valsartan	valsartan	valsartan
valsartan and hydrochlorothiazide	valsartan, hydrochlorothiazide	valsartan and hydrochlorothiazide
vandetanib	vandetanib	vandetanib
vardenafil	vardenafil hydrochloride	vardenafil
Vectibix	panitumumab	Vectibix
verteporfin	verteporfin	verteporfin
vildagliptin	vildagliptin	vildagliptin
vildagliptin and metformin	vildagliptin, metformin	vildagliptin and metformin
Vimovo	naproxen, esomeprazole	Vimovo
Visabelle	dienogest	Visabelle
Visanna	dienogest	Visanna
Visanne	dienogest	Visanne
Visannette	dienogest	Visannette
Visudyne	verteporfin	Visudyne
Vivanza	vardenafil hydrochloride	Vivanza
Vivelle	estradiol	Vivelle, Vivelledot, Estradot
Voltarol	diclofenac	Voltarol
Votubia	everolimus	Votubia
Xgeva	Denosumab	Xgeva
Xofigo	radium Ra 223 dichloride	Xofigo
Xolair	omalizumab	Xolair
Yaila	vardenafil hydrochloride	Yaila
Zactima	vandetanib	Zactima
Zaltrap	ziv-aflibercept	Zaltrap
Zinforo	Ceftaroline foramil	Zinforo
ziv-aflibercept	ziv-aflibercept	Aflibercept
zoledronic acid	zoledronic acid	zoledronic acid

zolmitriptan	zolmitriptan	zolmitriptan
Zolpidem	zolpidem	Zolpidem
Zometa	zoledronic acid	Zometa
Zomig	zolmitriptan	Zomig
Zomigon	zolmitriptan	Zomigon
Zomigoro	zolmitriptan	Zomigoro
Zykadia	ceritinib	Zykadia