Data Exchange

Data Engineering

Data Exchange

- XML (eXtensible Markup Language): A versatile and structured data format, commonly used in web services, configuration, and data interchange between languages with different data structures.
- HTML (HyperText Markup Language): The standard markup language for documents to be displayed in a web browser. While it's not typically used for data exchange, it's crucial when web scraping is required.
- JSON (JavaScript Object Notation): Lightweight and human-readable.
 Predominantly used in web APIs and config files because of its easy integration with most programming languages.

Why It Matters for Data Engineering:

- Interoperability: These formats facilitate communication between different systems, languages, and architectures, ensuring a smooth data exchange.
- Versatility: Different systems prefer different formats. A data engineer might need XML for a SOAP web service, JSON for a RESTful service, and HTML when scraping data from websites.
- Flexibility: They can represent complex hierarchical data structures, allowing for the representation of almost any data model.
- Ubiquity: Given their widespread use, understanding these formats is essential for integrating with a vast number of platforms and tools.

XML

XML stands for eXtensible Markup Language.

• It is a markup language that defines a set of rules for encoding documents in a format that is both human-readable and machine-readable.

Key Features:

- Semi-Structured Data: Enables the organization of data into nested, hierarchically structured documents.
- Self-descriptive: Tags describe the data and the data types, making it more interpretable.
- Platform-Independent: Works on any system, facilitating data interchange between incompatible systems.

```
<?xml version="1.0"
encoding="UTF-8"?>
cproducts>
  cproduct>
    <name>Laptop</name>
    <price>1000</price>
    <brand>Dell
    <stock>20</stock>
  </product>
  conduct>
    <name>Smartphone</name>
    <price>600</price>
    <br/>
<br/>
d>Apple</br/>
/brand>
    <stock>50</stock>
  </product>
  cproduct>
    <name>Desk Chair</name>
    <price>150</price>
    <brand>IKEA
    <stock>100</stock>
  </product>
</products>
```

Understanding the Structure of XML

Components of an XML Element:

- Element Name: Identifies the type of data, wrapped in angle brackets (<elementName>).
- Attributes: Additional descriptors within the opening tag (attribute="value").
- Child Elements: Elements nested within parent elements, forming a tree structure.
- Text Content: The actual data enclosed between the opening and closing tags.

XML Path Language

XPath is language designed for querying XML data.

Navigational Path Expressions

- /: Selects from the root node.
 Example: /bookstore selects the root element named product.
- //: Selects nodes from the current node that match the selection, regardless of their position.
 Example: //book selects all book elements in the document.
- Selects the current node.
 Example: . can be used to refer to the current node being processed within a loop.
- ...: Selects the parent of the current node. Example: .. selects the parent element of the current node.

Predicates

- []: Used to find a specific node or a node that contains a specific value.
 - Example: /bookstore/book[1] selects the first book element that is a child of bookstore.
- @: Selects attributes.

Example: /bookstore/book/@lang selects the lang attribute of the book element.

Logical and Comparison Operators

- |: Computes the union of two sequences.
 Example: /bookstore/book | //price selects all book elements under bookstore and all price elements in the document.
 - =: Checks for equality.
 - Example: /bookstore/book[price>30] selects all book elements under bookstore with a price of 30.
 - !=: Checks for inequality.
- Example: //price[@currency != 'USD'] selects all price elements that have a currency attribute not equal to 'USD'.
 - >, <, >=, <=: Comparison operators.
- Example: /bookstore/book[price > 30] selects all book elements under bookstore with a price greater than 30.

Functions

- text(): Selects the text content of a node.
 Example: //book/title/text() selects the text content of all title elements inside book.
- contains(): Checks if a node contains a specific string.
 Example: //book[contains(title, 'XML')] selects all book elements that have 'XML' within their title.

Example

```
import pandas as pd
from lxml import etree
# Parse the XML string
xml data = "our xml"
root = etree.fromstring(xml data)
# Use XPath to extract the desired elements
titles = root.xpath('//book/title/text()')
prices = root.xpath('//book/price/text()')
# Create a DataFrame
df = pd.DataFrame({
  'Title': titles.
  'Price': prices
})
```

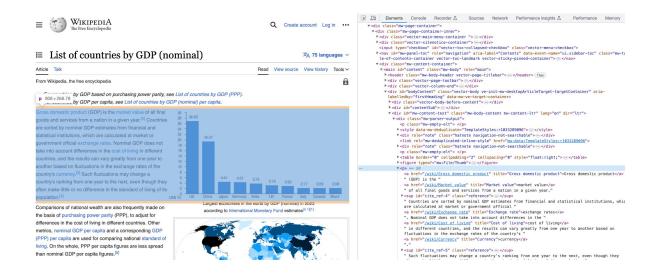
```
<data>
  <bookstore>
    <book>
       <title lang="en">Learning XML</title>
       <price currency="USD">29.95</price>
    </book>
    <book>
       <title lang="fr">Lire XML</title>
       <price currency="USD">39.95</price>
    </book>
  </bookstore>
</data>
```



HTML (HyperText Markup Language)

Key Components:

- Elements: Represent structural units, e.g., <body>, <div>, , <a>
- Attributes: Provide additional information about elements, e.g., class="intro".



Extracting GDP data from Wikipedia

The table initially ranks each country or territory with their latest available estimates, and can be reranked by either of the sources

The links in the "Country/Territory" row of the following table link to the article on the GDP or the economy of the respective country or territory.

GDP (USD million) by country

		• •	IMF ^[1]	[13]	World Ba	ank ^[14]	United Nations ^[15]		
	Country/Territory	♦ UN region	Estimate +	Year ≑	Estimate +	Year +	Estimate +	Year +	
	World	_	105,568,776	2023	100,562,011	2022	96,698,005	2021	
1	United States	Americas	26,854,599	2023	25,462,700	2022	23,315,081	2021	
2	China	Asia	19,373,586	[n 1]2023	17,963,171	[n 3]2022	17,734,131	^[n 1] 2021	
3	Japan	Asia	4,409,738	2023	4,231,141	2022	4,940,878	2021	
4	Germany	Europe	4,308,854	2023	4,072,192	2022	4,259,935	2021	
5	India India	Asia	3,736,882	2023	3,385,090	2022	3,201,471	2021	
6	United Kingdom	Europe	3,158,938	2023	3,070,668	2022	3,131,378	2021	
7	France	Europe	2,923,489	2023	2,782,905	2022	2,957,880	2021	
8	■ Italy	Europe	2,169,745	2023	2,010,432	2022	2,107,703	2021	
9	I ◆ I Canada	Americas	2,089,672	2023	2,139,840	2022	1,988,336	2021	
10	♦ Brazil	Americas	2,081,235	2023	1,920,096	2022	1,608,981	2021	
11	Russia	Europe	2,062,649	2023	2,240,422	2022	1,778,782	2021	
12	South Korea	Asia	1,721,909	2023	1,665,246	2022	1,810,966	2021	
13	*** Australia	Oceania	1,707,548	2023	1,675,419	2022	1,734,532	2021	
14	■ Mexico	Americas	1,663,164	2023	1,414,187	2022	1,272,839	2021	
15	Spain	Europe	1,492,432	2023	1,397,509	2022	1,427,381	2021	

https://en.wikipedia.org/wiki/List_of_countries_by_GDP_(nominal)

HTTP Request

Key Components:

- Method: Describes the desired action (e.g., GET, POST, PUT, DELETE).
- URL: The address to which the request is directed.
- Headers: Contains metadata for the HTTP request, such as user-agent, content-type, and more.
- Body: Contains data to be sent to the server (common in POST and PUT methods).

```
GET /wiki/Main_Page HTTP/1.1
Host: en.wikipedia.org
User-Agent: Mozilla/5.0 (Windows NT 10.0; Win64; x64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/85.0.4183.121 Safari/537.36
Accept: text/html,application/xhtml+xml,application/xml;q=0.9,image/webp,*/*;q=0.8
Accept-Language: en-US,en;q=0.5
Accept-Encoding: gzip, deflate, br
DNT: 1
Connection: keep-alive
Upgrade-Insecure-Requests: 1
Cache-Control: max-age=0
```

HTTP Response

Key Components:

- Status Code: Indicates the result of the request (e.g., 200 for OK, 404 for Not Found).
- Headers: Contains metadata about the response, like content-type, server details, and more.
- Body: Contains the data returned from the server, such as a webpage's HTML or API data.

```
import requests

wiki_url = 'https://en.wikipedia.org/wiki/List_of_countries_by_GDP_(nominal)'
wiki_resp = requests.get(wiki_url)

print(wiki_resp)
```

<Response [200]>

```
import requests
wiki_url = 'https://en.wikipedia.org/wiki/List_of_countries_by_GDP_(nominal)'
wiki_resp = requests.get(wiki_url)
print(wiki_resp)
<Response [200]>
from lxml import html
wiki_tree = html.fromstring(wiki_resp.content)
```

<Element html at 0x7e84e1fc5620>

print(wiki_tree)

```
tables = wiki_tree.xpath('//table')
for t in tables:
  print(t)
```

```
<Element table at 0x7e84e1fc62f0>
<Element table at 0x7e84e1fa8db0>
<Element table at 0x7e84e1fa8f40>
<Element table at 0x7e84e1fa9490>
<Element table at 0x7e84e1faafc0>
<Element table at 0x7e84e1faa750>
<Element table at 0x7e84e1fa89f0>
```

```
tables = wiki_tree.xpath('//table')
for t in tables:
  print(t)
```

```
<Element table at 0x7e84e1fc62f0>
<Element table at 0x7e84e1fa8db0>
<Element table at 0x7e84e1fa8f40>
<Element table at 0x7e84e1fa9490>
<Element table at 0x7e84e1faafc0>
<Element table at 0x7e84e1faa750>
<Element table at 0x7e84e1fa89f0>
```

```
wiki_tree.xpath('//table[2]/caption/text()')
```

['GDP (USD million) by country\n']

	_		IMF ^[1]	[13]	World Bank ^[14]		United Nat	tions ^[15]
	Country/Territory	UN region •	Estimate +	Year ♦	Estimate +	Year +	Estimate +	Year ♦
	a 84.05×16	-	105,568,776	2023	100,562,011	2022	96,698,005	2021
1	United States	Americas	26,854,599	2023	25,462,700	2022	23,315,081	2021
2	China	Asia	19,373,586	[n 1]2023	17,963,171	[n 3]2022	17,734,131	[n 1]2021
3	Japan	Asia	4,409,738	2023	4,231,141	2022	4,940,878	2021
4	Germany	Europe	4,308,854	2023	4,072,192	2022	4,259,935	2021
5	India	Asia	3,736,882	2023	3,385,090	2022	3,201,471	2021
6	United Kingdom	Europe	3,158,938	2023	3,070,668	2022	3,131,378	2021
7	France	Europe	2,923,489	2023	2,782,905	2022	2,957,880	2021
8	■ Italy	Europe	2,169,745	2023	2,010,432	2022	2,107,703	2021
9	■◆■ Canada	Americas	2,089,672	2023	2,139,840	2022	1,988,336	2021
10	Rrazil	Americae	2 081 235	2023	1 020 006	2022	1 608 081	2021

```
▼
▶ ··· 
 -
 105,568,776
 2023
 100,562,011
 2022
 96,698,005
 2021 
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 ::before
 ▼ == $0
 ><span class="flagicon" style="display:inline-block;width:25px;text-align:left">:=></span>
  <a href="/wiki/Economy of the United States" title="Economy of the United States">United
  States</a>
 ▼
  <a href="/wiki/Americas" title="Americas">Americas</a>
 26.854.599
 2023
```

```
country_name = wiki_tree.xpath('//table[2]/tbody/tr/td[1]/a/text()')
region_name = wiki_tree.xpath('//table[2]/tbody/tr/td[2]/a/text()')
```

			IMF ^{[1][13]}		World Ba	World Bank ^[14]		United Nations[15]	
	Country/Territory	UN region •	Estimate +	Year ♦	Estimate +	Year +	Estimate +	Year ♦	
	a 84.05×16	-	105,568,776	2023	100,562,011	2022	96,698,005	2021	
1	United States	Americas	26,854,599	2023	25,462,700	2022	23,315,081	2021	
2	China	Asia	19,373,586	[n 1]2023	17,963,171	[n 3]2022	17,734,131	[n 1]2021	
3	Japan	Asia	4,409,738	2023	4,231,141	2022	4,940,878	2021	
4	Germany	Europe	4,308,854	2023	4,072,192	2022	4,259,935	2021	
5	India	Asia	3,736,882	2023	3,385,090	2022	3,201,471	2021	
6	United Kingdom	Europe	3,158,938	2023	3,070,668	2022	3,131,378	2021	
7	France	Europe	2,923,489	2023	2,782,905	2022	2,957,880	2021	
8	■ Italy	Europe	2,169,745	2023	2,010,432	2022	2,107,703	2021	
9	■ Canada	Americas	2,089,672	2023	2,139,840	2022	1,988,336	2021	
10	Rrazil	Americae	2 081 235	2023	1 020 006	2022	1 608 981	2021	

```
▼
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 -
 105,568,776
 2023
 100,562,011
 2022
 96,698,005
 2021 
▼
 ::before
 ▼ == $0
 ><span class="flagicon" style="display:inline-block;width:25px;text-align:left">:=></span>
  <a href="/wiki/Economy of the United States" title="Economy of the United States">United
  States</a>
 ▼
  <a href="/wiki/Americas" title="Americas">Americas</a>
 26.854.599
 2023
```

```
country_name = wiki_tree.xpath('//table[2]/tbody/tr/td[1]/a/text()')
region_name = wiki_tree.xpath('//table[2]/tbody/tr/td[2]/a/text()')
```

```
world_bank_est = wiki_tree.xpath('//table[2]/tbody/tr/td[5]/text()')
```

```
country_name = wiki_tree.xpath('//table[2]/tbody/tr/td[1]/a/text()')
region_name = wiki_tree.xpath('//table[2]/tbody/tr/td[2]/a/text()')
```

```
world_bank_est = wiki_tree.xpath('//table[2]/tbody/tr/td[5]/text()')
```

worldbank_df = pd.DataFrame({'Country': country_name, 'Region': region_name,
'Estimate': world_bank_est[1:]});

	Country	Region	Estimate			
0	United States	Americas	25,462,700			
1	China	Asia	17,963,171			
2	Japan	Asia	4,231,141			
3	Germany	Europe	4,072,192			
4	India	Asia	3,385,090			
208	Anguilla	Americas	303			
209	Kiribati	Oceania	223			
210	Nauru	Oceania	151			
211	Montserrat	Americas	72			
212	Tuvalu	Oceania	60			
213 rc	213 rows × 3 columns					

worldbank_df[worldbank_df['Estimate'] == '-']

	Country	Region	Estimate
20	Taiwan	Asia	_
71	Venezuela	Americas	_
75	Turkmenistan	Asia	_
127	Yemen	Asia	_
160	South Sudan	Africa	_
171	Aruba	Americas	_
179	Bhutan	Asia	_
180	Eritrea	Africa	_
189	San Marino	Europe	_
203	Tonga	Oceania	-
207	Palau	Oceania	_

```
nworldbank_df = worldbank_df[worldbank_df['Estimate'] == '-']
nworldbank_df['Estimate'] = nworldbank_df['Estimate'].apply(lambda x:
float(str(x).replace(',','')))
```

	-		
0	United States	Americas	25462700.0
1	China	Asia	17963171.0
2	Japan	Asia	4231141.0
3	Germany	Europe	4072192.0
4	India	Asia	3385090.0
		1	
208	Anguilla	Americas	303.0
209	Kiribati	Oceania	223.0
210	Nauru	Oceania	151.0
211	Montserrat	Americas	72.0
212	Tuvalu	Oceania	60.0
202 ro	ws × 3 columns		

Country Region Estimate

```
region_gpd_stats = nworldbank_df.groupby('Region').agg({'Estimate': ['mean',
'sum' ,'max','min']}).reset_index()
region_gpd_stats.columns = ['Region', 'Mean', 'Sum', 'Max', 'Min']
```

	Region	Mean	Sum	Max	Min
0	Africa	55473.396226	2940090.0	477386.0	547.0
1	Americas	759319.136364	33410042.0	25462700.0	72.0
2	Asia	797008.978261	36662413.0	17963171.0	2022.0
3	Europe	540130.409091	23765738.0	4072192.0	3352.0
4	Oceania	131949.066667	1979236.0	1675419.0	60.0

REST: REpresentational State Transfer

- Statelessness: Every request from a client to a server must contain all information needed to understand and process the request.
- Client-Server: A separation of concerns. The client handles the user interface, while the server manages the backend and data.
- Cacheable: Responses can be cached, implying that some responses are reusable for identical requests in the future.

HTTP Methods (CRUD operations):

GET: Retrieve data.
POST: Add new data.

PUT/PATCH: Update existing data.

DELETE: Remove data.

Example: Finding Influential Papers

```
import requests
r =requests.get('https://api.semanticscholar.org/graph/v1/author/search',
          params={'query': "Geoffrey E. Hinton"})
r.content
                                                                                                                                        SEMANTIC SCHOLAR Search 214,066,055 papers from all fields of science
                                                                                                                                                                                                                                  Create Free Accour
  {'total': 3,
   'offset': 0.
                                                                                                                                                                      Publications
                                                                                                                                                                                       Citing Authors →
                                                                                                                                                                                                         Referenced Authors ->
                                                                                                                                                                                                                           Co-Authors →
                                                                                                                                         Geoffrev E. Hinton
                                                                                                                                                                      485
                                                                                                                                                                                        625,219
                                                                                                                                                                                                         9,401
                                                                                                                                                                                                                           570
   'data': [{'authorld': '116210976',
                                                                                                                                                                                     Co-Author ~
                                                                                                                                                                                                        More Filters
                                                                                                                                                                                                                    Sort by Most Influe... V
                                                                                                                                         h-index
                                                                                                                                                            159
  'name': 'E. Geoffrey'},
                                                                                                                                                         494,390
                                                                                                                                         Highly Influential Citations 41,596
                                                                                                                                                                    ImageNet classification with deep convolutional neural networks
    {'authorId': '50286838', 'name':
                                                                                                                                                                    A. Krizhevsky, Ilya Sutskever, Geoffrey E. Hinton · Computer Science · Communications of the ACM
                                                                                                                                               Follow Author...
                                                                                                                                                                    3 December 2012
                                                                                                                                                                     TLDR A large, deep convolutional neural network was trained to classify the 1.2 million high-
                                                                                                                                              Claim Author Page
  'James E. . Hinton'},
                                                                                                                                                                    resolution images in the ImageNet LSVRC-2010 contest into the 1000 different classes and employed
                                                                                                                                                                    a recently developed regularization method called "dropout" that proved to be very effective. Expand
    {'authorId': '1695689', 'name':
                                                                                                                                                                     Author pages are created from data
                                                                                                                                         sourced from our academic... show more
                                                                                                                                                                    Dropout: a simple way to prevent neural networks from overfitting
  'Geoffrey E. Hinton'}]
                                                                                                                                                                    Nitish Srivastava, Geoffrey E. Hinton, A. Krizhevsky, Ilva Sutskever, R. Salakhutdinov · Computer Science
                                                                                                                                                                    Journal of machine learning research - 2014
                                                                                                                                      Co-Authors
                                                                                                                                                                     TLDR It is shown that dropout improves the performance of neural networks on supervised learning
                                                                                                                                                                    tasks in vision, speech recognition, document classification and computational biology, obtaining
                                                                                                                                           Geoffrey I. Webb
                                                                                                                                                                    state-of-the-art results on many benchmark data sets. Expand
                                                                                                                                           214 Publications + 2 185 Citations
                                                                                                                                                                     C. Sammut
authorId = matched_authors['data'][2]['authorId'])
                                                                                                                                           379 Publications • 5,982 Citations
                                                                                                                                                                    A Simple Framework for Contrastive Learning of Visual Representations
                                                                                                                                                                    Ting Chen, Simon Kornblith, Mohammad Norouzi, Geoffrey E. Hinton · Computer Science
print(authorId)
                                                                                                                                           Yee Whye Teh
                                                                                                                                                                    International Conference on Machine Learning · 13 February 2020
                                                                                                                                           33 Publications · 342 Citations
                                                                                                                                                                     TLDR It is shown that composition of data augmentations plays a critical role in defining effective
```

```
r = requests.get(
  'https://api.semanticscholar.org/graph/v1/author/' + authorId,
  params={'fields':'name,paperCount,citationCount,papers.title,papers.influentialCitationCount'})
paper_json = r.json()
```

• authorId - S2 unique ID for this author

external Ids - ORCID/DBI P IDs for this author, if known

```
• url - URL on the Semantic Scholar website
{'authorId': '1695689',

    name - Author's name

 'name': 'Geoffrey E. Hinton',

    aliases - List of names the author has used on publications over time, not intended to be displayed to users.

 'paperCount': 484,
                                                                                                                         WARNING: this list may be out of date or contain deadnames of authors who have changed their name, (see
                                                                                                                         https://en.wikipedia.org/wiki/Deadnaming)
 'citationCount': 493491,
                                                                                                                       • affiliations - Author's affiliations - sourced from claimed authors who have set affiliation on their S2 author page
 'papers': [{'paperId': '40b736b8a628504a9463130705f8012d2e5e5560',
                                                                                                                         homepage - Author's homepage
   'title': 'Robust and data-efficient generalization of self-supervised machine learning for d
                                                                                                                         paperCount - Author's total publications count
   'influentialCitationCount': 0},

    citationCount - Author's total citations count

  {'paperId': '944ab9578916572cd3896b2452dc89ba8ff2e8a9',

    hIndex - See the S2 FAQ on h-index

   'title': 'CogSci 2020 Developing a Mind: Learning in Humans, Animals, and Machines',
                                                                                                                       · citations

    paperId - Always included, A unique (string) identifier for this paper

   'influentialCitationCount': 0},

    corpusId - A second unique (numeric) identifier for this paper

  {'paperId': 'd26f928defed8d10a374d587cfdfb7b256d30c82',

    url - URL on the Semantic Scholar website

   'title': 'UVA-DARE (Digital Academic Repository) A model of prenatal acquisition of vowels',

    title - Included if no fields are specified

   'influentialCitationCount': 0},

    venue - Normalized venue name

  {'paperId': '06761cb27e14aa55a6c3d98b949898aa26416698',
                                                                                                                           o publicationVenue - Publication venue meta-data for the paper
   'title': 'A Unified Sequence Interface for Vision Tasks'.

    vear - Year of publication

                                                                                                                           o authors - Up to 500 will be returned. Will include: authorId & name
   'influentialCitationCount': 9},

    To get more detailed information about an author's papers, use the /author/{author id}/papers endpoint

  {'paperId': '37ba9c33025fb31f25436010e12c65a0bafc0e1f'.

    Total number of citations will be truncated at 10,000 for the entire batch

   'title': 'Meta-Learning Fast Weight Language Models'.

    To fetch more citations per paper, reduce the number of papers in the batch with limit= or use the

   'influentialCitationCount': 0},
                                                                                                                             /paper/{paper id}/citations endpoint
  {'paperId': '39e2f96723e41b38d7bf1bef6825506d7b5394c8'.

    references

   'title': 'Neural Networks'.
                                                                                                                           o paperId - Always included. A unique (string) identifier for this paper
   'influentialCitationCount': 0},
                                                                                                                           o corpusId - A second unique (numeric) identifier for this paper
                                                                                                                           o url - URL on the Semantic Scholar website
  {'paperId': '614dde18483338069d482d7452900c28052aba83'.

    title - Included if no fields are specified

   'title': 'A Generalist Framework for Panoptic Segmentation of Images and Videos'.

    venue - Normalized venue name

   'influentialCitationCount': 6},
                                                                                                                           o publicationVenue - Publication venue meta-data for the paper
  {'paperId': '75e3475cf49caf1dbbcad526b0132b455dc88dd5'.

    vear - Year of publication

   'title': 'The Forward-Forward Algorithm: Some Preliminary Investigations'.
                                                                                                                           o authors - Up to 500 will be returned. Will include: authorId & name

    To get more detailed information about an author's papers, use the /author/{author id}/papers endpoint

   'influentialCitationCount': 11}.

    Same fields supported as for papers above

    Total number of references will be truncated at 10.000 for the entire batch.

                                                                                                                           o To fetch more references per paper, reduce the number of papers in the batch with limit= or use the
                                                                                                                             /paper/{paper id}/references endpoint.
```

pandas.json_normalize

```
pandas.json_normalize(data, record_path=None, meta=None,
meta_prefix=None, record_prefix=None, errors='raise', sep='.',
max_level=None)
```

Normalize semi-structured JSON data into a flat table.

Parameters:

data: dict or list of dicts

record_path: str or list of str, default None

Path in each object to list of records. If not passed, data will be assumed to be an array of records.

meta: list of paths (str or list of str), default None

Fields to use as metadata for each record in resulting table.

```
pd.json_normalize(paper_json)
```

```
        authorId
        name
        paperCount
        citationCount
        papers

        0
        1695689
        Geoffrey E. Hinton
        484
        493491
        [{'paperId': '40b736b8a628504a9463130705f8012d...}
```

pd.json_normalize(paper_json)

	authorId	name	paperCount	citationCount	papers
0	1695689	Geoffrey E. Hinton	484	493491	[{'paperld': '40b736b8a628504a9463130705f8012d

pd.json_normalize(paper_json, record_path="papers")

	paperId	title	${\tt influentialCitationCount}$
0	40b736b8a628504a9463130705f8012d2e5e5560	Robust and data-efficient generalization of se	0
1	944ab9578916572cd3896b2452dc89ba8ff2e8a9	CogSci 2020 Developing a Mind: Learning in Hum	0
2	d26f928defed8d10a374d587cfdfb7b256d30c82	UvA-DARE (Digital Academic Repository) A model	0
3	06761cb27e14aa55a6c3d98b949898aa26416698	A Unified Sequence Interface for Vision Tasks	9
4	37ba9c33025fb31f25436010e12c65a0bafc0e1f	Meta-Learning Fast Weight Language Models	0
480	2b114f4d05494fceb22473fcd29d940e9aa52bf4	Rectified Linear Units Improve Restricted Boltz	60
481	3e5d838aef4aea3ff22a744f292cfb4094909e35	COOPERATIVE : COMPUTATION	0
482	5f75f39caf0ad58afd117ec14266658a7e504781	Using mixtures of deformable models to capture	0
483	88d214e9fb00e58a7b504c88be0af4b4d07c624f	Maximizing Mutual Information	0
484	f1fa5a8addd84be5a0e0382772c807d1ebcf0476	7. Conclusion and Future Work Novel Objective \dots	0

pd.json_normalize(paper_json, record_path="papers", meta=['authorId'])

	paperId	title	${\tt influentialCitationCount}$	authorId
0	40b736b8a628504a9463130705f8012d2e5e5560	Robust and data-efficient generalization of se	0	1695689
1	944ab9578916572cd3896b2452dc89ba8ff2e8a9	CogSci 2020 Developing a Mind: Learning in Hum	0	1695689
2	d26f928defed8d10a374d587cfdfb7b256d30c82	UvA-DARE (Digital Academic Repository) A model	0	1695689
3	06761cb27e14aa55a6c3d98b949898aa26416698	A Unified Sequence Interface for Vision Tasks	9	1695689
4	37ba9c33025fb31f25436010e12c65a0bafc0e1f	Meta-Learning Fast Weight Language Models	0	1695689
480	2b114f4d05494fceb22473fcd29d940e9aa52bf4	Rectified Linear Units Improve Restricted Boltz	60	1695689
481	3e5d838aef4aea3ff22a744f292cfb4094909e35	COOPERATIVE : COMPUTATION	0	1695689
482	5f75f39caf0ad58afd117ec14266658a7e504781	Using mixtures of deformable models to capture	0	1695689
483	88d214e9fb00e58a7b504c88be0af4b4d07c624f	Maximizing Mutual Information	0	1695689

7. Conclusion and Future Work Novel Objective ...

f1fa5a8addd84be5a0e0382772c807d1ebcf0476

484

hinton_papers = pd.json_normalize(paper_json, record_path="papers", meta=['authorId'])

hinton_papers.sort_values(by=['influentialCitationCount	t'],asc	<pre>ending=False).head()</pre>	
paperId	title	influentialCitationCount	authorId

ImageNet classification with deep convolutiona...

Dropout: a simple way to prevent neural networ...

A Simple Framework for Contrastive Learning of...

Distilling the Knowledge in a Neural Network

Deep Learning

13169

2704

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71

abd1c342495432171beb7ca8fd9551ef13cbd0ff

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a4cec122a08216fe8a3bc19b22e78fbaea096256

0c908739fbff75f03469d13d4a1a07de3414ee19