Natural Language Processing with Machine Learning

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In this project, we performed Named entity recognition (NER). Data of this project: Medical text data is a record containing detailed clinical data. Named entity recognition is the basis of text information processing and is an important part of extracting valuable information in medical texts. The named entity recognition technology can accurately identify the information needed in medical texts and help medical staff make clinical decision-making, evidence-based medicine, and epidemic disease monitoring.

First, we installed certain libraries to perform operations on our data set. Pandas, one of these libraries, is used to perform operations on the dataset. The most important are scispacy and spacy for medical procedures.

Spacy: It is an open-source NLP library that provides out-of-the-box models for various domains, including the medical domain.
Scispacy: A specialized version of spacy that is trained specifically on scientific and biomedical text, which makes it ideal for processing medical text.

```
!pip install spacy
```

```
!pip install scispacy
```

```
Collecting scispacy
```

```
import pandas as pd
import numpy as np
import spacy
```

We load a pandas dataframe by reading its data and then displaying the first few rows of this dataset.

```
med = pd.read_csv('mtsamples.csv', index_col=0)
med.head()
```

	description	medical_specialty	sample_name	transcription	keywords
0	A 23-year-old white female presents with comp...	Allergy / Immunology	Allergic Rhinitis	SUBJECTIVE:, This 23-year-old white female pr...	allergy / immunology, allergic rhinitis, aller...
1	Consult for laparoscopic gastric bypass.	Bariatrics	Laparoscopic Gastric Bypass Consult - 2	PAST MEDICAL HISTORY:, He has difficulty climb...	bariatrics, laparoscopic gastric bypass, weigh...
2	Consult for laparoscopic gastric bypass.	Bariatrics	Laparoscopic Gastric Bypass Consult - 1	HISTORY OF PRESENT ILLNESS: , I have seen ABC ...	bariatrics, laparoscopic gastric bypass, heart...
3	2-D M-Mode. Doppler.	Cardiovascular / Pulmonary	2-D Echocardiogram - 1	2-D M-MODE: , ,1. Left atrial enlargement wit...	cardiovascular / pulmonary, 2-d m-mode, dopple...
4	2-D Echocardiogram	Cardiovascular / Pulmonary	2-D Echocardiogram - 2	1. The left ventricular cavity size and wall ...	cardiovascular / pulmonary, 2-d, doppler, echo...

Process to check for null values on data set and find the number of null values in each column:

```
med.isnull().sum()
```

```
description            0
medical_specialty      0
sample_name            0
transcription         33
keywords            1068
dtype: int64
```

Shows the total number of rows and columns of the data set. In this here, there are 4999 rows and 5 columns.

```
med.shape
```

```
(4999, 5)
```

We used info to get more information about our dataset.

```
med.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 4999 entries, 0 to 4998
Data columns (total 5 columns):
 #   Column             Non-Null Count  Dtype 
---  ------             --------------  ----- 
 0   description        4999 non-null   object
 1   medical_specialty  4999 non-null   object
 2   sample_name        4999 non-null   object
 3   transcription      4966 non-null   object
 4   keywords           3931 non-null   object
dtypes: object(5)
memory usage: 234.3+ KB
```

We perform preliminary processing and editing on our data set. We used the "re" (regular expression) module to edit text data in the transcription column in a dataframe.

```
import re

med['transcription'] = med['transcription'].astype('str')
med['transcription'] = med['transcription'].apply(lambda x: re.sub('(\.,)', ". ", x))
```

"en_core_med7_lg" is a spacy model and is a language processing model specifically trained to work on medical texts. This model stands out for its ability to recognize named entities in medical texts, and we use it in our project. The "med7" in the model name refers to the model's ability to understand and recognize 7 main medical entity classes. These classes generally include diseases, drugs, symptoms, signs, procedures, microorganisms, and anatomical structures. We use it to perform tasks such as extracting important information from medical texts and recognizing disease or drug names.

```
!pip install https://huggingface.co/kormilitzin/en_core_med7_lg/resolve/main/en_core_med7_lg-any-py3-none-any.whl
```

```
Collecting en-core-med7-lg==any
```

```
#import en_ner_bc5cdr_md
import en_core_med7_lg
```

```
/usr/local/lib/python3.10/dist-packages/spacy/util.py:910: UserWarning: [W095] Model 'en_core_med7_lg' (3.4.2.1) was trained with spaCy v3.4.2 and may not be
on (3.6.1). If you see errors or degraded performance, download a newer compatible model or retrain your custom model with the current spaCy version. For more
ython -m spacy validate
```

Using the Spacy language model called "en_core_med7_lg", we defined a function (generate_annotation) to identify named entities and tags in medical texts. This function runs on a data set and creates a list containing entity information about the texts.

```
nlp = spacy.load("en_core_med7_lg")

# This function generate anotation for each entities and label
def generate_annotation(texts):
    annotations = []
    for text in texts:
        doc = nlp(text)
        entities = []
        for ent in doc.ents:
            entities.append((ent.start_char, ent.end_char, ent.label_))
        annotations.append((text, {'entities': entities}))
    return annotations

# Extract text entities and labels from the dataset (transcription)
medical_doc = med['transcription'].tolist()

# Let's generate annotations
annotations = generate_annotation(medical_doc)

# Let's print documents and annotations
print("Document:")
print(annotations[0][0]) # first document text
print("Annotations:")
print(annotations[0][1]) # annotation for the first document
```

```
/usr/local/lib/python3.10/dist-packages/spacy/util.py:910: UserWarning: [W095] Model 'en_core_med7_lg' (3.4.2.1) was trained with spaCy
v3.4.2 and may not be 100% compatible with the current version (3.6.1). If you see errors or degraded performance, download a newer com
patible model or retrain your custom model with the current spaCy version. For more details and available updates, run: python -m spacy
validate
```

```
Document:
SUBJECTIVE:,  This 23-year-old white female presents with complaint of allergies.  She used to have allergies when she lived in Seattle
but she thinks they are worse here.  In the past, she has tried Claritin, and Zyrtec.  Both worked for short time but then seemed to lo
se effectiveness.  She has used Allegra also.  She used that last summer and she began using it again two weeks ago.  It does not appea
r to be working very well.  She has used over-the-counter sprays but no prescription nasal sprays.  She does have asthma but doest not
require daily medication for this and does not think it is flaring up. MEDICATIONS: , Her only medication currently is Ortho Tri-Cyclen
and the Allegra. ALLERGIES: , She has no known medicine allergies. OBJECTIVE:,Vitals:  Weight was 130 pounds and blood pressure 124/78.
HEENT:  Her throat was mildly erythematous without exudate.  Nasal mucosa was erythematous and swollen.  Only clear drainage was seen.
TMs were clear. Neck:  Supple without adenopathy. Lungs:  Clear. ASSESSMENT:,  Allergic rhinitis. PLAN:,1.  She will try Zyrtec instead
of Allegra again.  Another option will be to use loratadine.  She does not think she has prescription coverage so that might be cheape
r. 2.  Samples of Nasonex two sprays in each nostril given for three weeks.  A prescription was written as well.
Annotations:
{'entities': [(200, 208, 'DRUG'), (214, 220, 'DRUG'), (549, 554, 'FREQUENCY'), (1070, 1076, 'DRUG'), (1134, 1144, 'DRUG'), (1237, 1244,
'DRUG'), (1245, 1248, 'DOSAGE'), (1249, 1255, 'FORM'), (1259, 1263, 'DOSAGE'), (1278, 1293, 'DURATION')]}
```

Let's visualize the labels of the text and display each label in a different color. options line: This line creates a dictionary that determines the properties of the visualization. The ents property contains the types of tags to display. The colors property contains the col_dict dictionary, which contains the color code of each label.

```
from spacy import displacy
nlp = spacy.load("en_core_med7_lg")

# Create distict colours for labels

col_dict = {}
s_colours = ['#e6194B', '#3cb44b', '#ffe119', '#ffd8b1', '#f58231', '#f032e6', '#42d4f4']
for label, colour in zip(nlp.pipe_labels['ner'], s_colours):
    col_dict[label] = colour

options = {'ents': nlp.pipe_labels['ner'], 'colors':col_dict}

transcription = med['transcription'][0]
doc = nlp(transcription)

spacy.displacy.render(doc, style = 'ent', jupyter = True, options = options)

[(ent.text, ent.label_) for ent in doc.ents]
```

SUBJECTIVE:, This 23-year-old white female presents with complaint of allergies. She used to have allergies when she lived in Seattle but she thinks they are worse here. In the past, she has tried Claritin DRUG , and Zyrtec DRUG . Both worked for short time but then seemed to lose effectiveness. She has used Allegra also. She used that last summer and she began using it again two weeks ago. It does not appear to be working very well. She has used over-the-counter sprays but no prescription nasal sprays. She does have asthma but doest not require daily FREQUENCY medication for this and does not think it is flaring up. MEDICATIONS: , Her only medication currently is Ortho Tri-Cyclen and the Allegra. ALLERGIES: , She has no known medicine allergies. OBJECTIVE:,Vitals: Weight was 130 pounds and blood pressure 124/78. HEENT: Her throat was mildly erythematous without exudate. Nasal mucosa was erythematous and swollen. Only clear drainage was seen. TMs were clear. Neck: Supple without adenopathy. Lungs: Clear. ASSESSMENT:, Allergic rhinitis. PLAN:,1. She will try Zyrtec DRUG instead of Allegra again. Another option will be to use loratadine DRUG . She does not think she has prescription coverage so that might be cheaper. 2. Samples of Nasonex DRUG two DOSAGE sprays FORM in each DOSAGE nostril given for three weeks DURATION . A prescription was written as well.

```
6]: [('Claritin', 'DRUG'),
     ('Zyrtec', 'DRUG'),
     ('daily', 'FREQUENCY'),
     ('Zyrtec', 'DRUG'),
     ('loratadine', 'DRUG'),
     ('Nasonex', 'DRUG'),
     ('two', 'DOSAGE'),
     ('sprays', 'FORM'),
     ('each', 'DOSAGE'),
     ('for three weeks', 'DURATION')]
```

To analyze the data set:

```
med_adj = med.sample(n=111, replace = False, random_state=42)
```

"en_ner_bc5cdr_md" this model was trained in 'en' English for the purpose of recognizing named entities in biomedical and clinical data. designed to print the positions and types of these entities in the text

```
pip install https://s3-us-west-2.amazonaws.com/ai2-s2-scispacy/releases/v0.5.3/en_ner_bc5cdr_md-0.5.3.tar.gz
```

```
Collecting https://s3-us-west-2.amazonaws.com/ai2-s2-scispacy/releases/v0.5.3/en_ner_bc5cdr_md-0.5.3.tar.gz
  Downloading https://s3-us-west-2.amazonaws.com/ai2-s2-scispacy/releases/v0.5.3/en_ner_bc5cdr_md-0.5.3.tar.gz (119.8 MB)
     ---------------------------------------- 119.8/119.8 MB 5.3 MB/s eta 0:00:00
```

```
!pip install https://s3-us-west-2.amazonaws.com/ai2-s2-scispacy/releases/v0.4.0/en_core_sci_sm-0.4.0.tar.gz --user
!pip install https://s3-us-west-2.amazonaws.com/ai2-s2-scispacy/releases/v0.4.0/en_ner_bc5cdr_md-0.4.0.tar.gz --user
!pip install https://s3-us-west-2.amazonaws.com/ai2-s2-scispacy/releases/v0.4.0/en_core_sci_lg-0.4.0.tar.gz --user
```

Retrieves the text of the second line from the "transcription" column. It creates a Spacy document by passing it through the NLP model. This document contains named entities from the text. It recognizes named entities by going through transcripts and prints the text content and tags of these entities to the screen.

```python
nlp = spacy.load("en_ner_bc5cdr_md")

transcription = med['transcription'].iloc[1]
doc= nlp(transcription)

# Let's extract and print all the entity
for ent in doc.ents:
    print(f"Text: {ent.text}, Entity Type: {ent.label_}")
    #print(f"Text: {ent.text}, Start: {ent.start_char}, End: {ent.end_char}, Entity Type: {ent.label_}") you can also use this
```

```
Text: pains, Entity Type: DISEASE
Text: knee pain, Entity Type: DISEASE
Text: pain, Entity Type: DISEASE
Text: pain, Entity Type: DISEASE
Text: reflux disease, Entity Type: DISEASE
Text: Heart disease, Entity Type: DISEASE
Text: stroke, Entity Type: DISEASE
Text: diabetes, Entity Type: DISEASE
Text: obesity, Entity Type: DISEASE
Text: hypertension, Entity Type: DISEASE
Text: allergic, Entity Type: DISEASE
Text: Penicillin, Entity Type: CHEMICAL
Text: chest pain, Entity Type: DISEASE
Text: coronary artery disease, Entity Type: DISEASE
Text: congestive heart failure, Entity Type: DISEASE
Text: arrhythmia, Entity Type: DISEASE
Text: atrial fibrillation, Entity Type: DISEASE
Text: cholesterol, Entity Type: CHEMICAL
Text: pulmonary embolism, Entity Type: DISEASE
Text: CVA, Entity Type: CHEMICAL
Text: venous insufficiency, Entity Type: DISEASE
Text: thrombophlebitis, Entity Type: DISEASE
Text: shortness of breath, Entity Type: DISEASE
Text: COPD, Entity Type: DISEASE
Text: emphysema, Entity Type: DISEASE
Text: sleep apnea, Entity Type: DISEASE
Text: diabetes, Entity Type: DISEASE
Text: swelling, Entity Type: DISEASE
Text: osteoarthritis, Entity Type: DISEASE
Text: rheumatoid arthritis, Entity Type: DISEASE
Text: hernia, Entity Type: DISEASE
Text: gallstones, Entity Type: DISEASE
Text: pancreatitis, Entity Type: DISEASE
Text: fatty liver, Entity Type: DISEASE
Text: hepatitis, Entity Type: DISEASE
Text: hemorrhoids, Entity Type: DISEASE
Text: bleeding, Entity Type: DISEASE
Text: polyps, Entity Type: DISEASE
Text: incontinence, Entity Type: DISEASE
Text: urinary stress incontinence, Entity Type: DISEASE
Text: cancer, Entity Type: DISEASE
Text: cellulitis, Entity Type: DISEASE
Text: pseudotumor, Entity Type: DISEASE
Text: meningitis, Entity Type: DISEASE
Text: encephalitis, Entity Type: DISEASE
```

This code detects patterns related to specific drug doses in medical texts and prints matches that match these patterns. It adds a match category called "DRUG_DOSE" and adds the patterns determined in the previous step to this category.

```
from  spacy.matcher import Matcher

# Let's load the model
nlp = spacy.load("en_core_med7_lg")

patterns = [
    [{"ENT_TYPE": "DRUG"}, {"LIKE_NUM": True}, {"IS_ASCII": True}],
    [{"LOWER": {"IN": ["mg", "g", "ml"]}}, {"ENT_TYPE": "DRUG"}],
    [{"ENT_TYPE": "DRUG"}, {"IS_DIGIT": True, "OP": "?"}, {"LOWER": {"IN": ["mg", "g", "ml"]}}]
]

matcher = Matcher(nlp.vocab)
matcher.add("DRUG_DOSE", patterns)

for transcription in  med_adj['transcription']:
    doc = nlp(transcription)
    matches = matcher(doc)
    for match_id, start, end in matches:
        string_id = nlp.vocab.strings[match_id]
        span = doc[start:end]
        print(string_id, start, end, span.text)
```

```
DRUG_DOSE 514 517 Diastat 20 mg
DRUG_DOSE 518 521 Topamax 25 mg
DRUG_DOSE 532 535 Tranxene 15 mg
DRUG_DOSE 538 541 Depakote 125 mg
DRUG_DOSE 729 732 Depacon 250 mg
DRUG_DOSE 266 269 Pepcid 40 mg
DRUG_DOSE 109 112 furosemide 40 mg
DRUG_DOSE 897 900 diltiazem 120 mg
DRUG_DOSE 433 436 Aspirin 325 mg
DRUG_DOSE 443 446 Lisinopril 40 mg
DRUG_DOSE 453 456 Felodipine 10 mg
DRUG_DOSE 465 468 Con 20 mEq
DRUG_DOSE 475 478 Omeprazole 20 mg
DRUG_DOSE 488 491 MiraLax 17 g
DRUG_DOSE 498 501 Lasix 20 mg
DRUG_DOSE 282 285 Omeprazole 40 mg
DRUG_DOSE 25 28 Prozac 20 mg
DRUG_DOSE 274 277 Rocephin 250 mg
DRUG_DOSE 278 281 azithromycin 1000 mg
DRUG_DOSE 504 507 Coumadin 5 mg
DRUG_DOSE 524 527 Aspirin 81 mg
DRUG_DOSE 533 536 Hydrochlorothiazide 25 mg
DRUG_DOSE 542 545 Plendil 10 mg
DRUG_DOSE 550 553 Lipitor 40 mg
DRUG_DOSE 955 958 dexamethasone 4 mg
DRUG_DOSE 286 289 Plavix 75 mg
DRUG_DOSE 294 297 metoprolol 25 mg
DRUG_DOSE 302 305 Flomax 0.4 mg
DRUG_DOSE 310 313 Zocor 20 mg
DRUG_DOSE 327 330 lisinopril 10 mg
DRUG_DOSE 78 81 iCAD Second Look
DRUG_DOSE 334 337 iCAD Second Look
DRUG_DOSE 27 30 fentanyl 25 mcg
DRUG_DOSE 100 103 Xylocaine 1%
DRUG_DOSE 66 69 Lexiscan 0.4 mg
DRUG_DOSE 187 190 lidocaine 2%
DRUG_DOSE 194 197 Marcaine 1.7 mL
DRUG_DOSE 258 261 Plaquenil 200 mg
DRUG_DOSE 268 271 Fosamax 170 mg
DRUG_DOSE 290 293 acid 1 mg
DRUG_DOSE 299 302 Trilisate 1000 mg
DRUG_DOSE 320 323 Hydrochlorothiazide 15 mg
DRUG_DOSE 330 333 Lopressor 50 mg
DRUG_DOSE 344 347 Trazodone 100 mg
```

We analyze our data set by dividing it into clusters due to its size.

```
med_adj = med.sample(n=3, replace = False, random_state=42)
```

It checks for the presence of certain category words (keywords) for each medical transcription text, and also extracts named entities using the Spacy language model and prints this information to the screen. Identifies named entities in text and returns a list containing the text and tags of these entities.

```
# Let's load our pretrained spacy model

nlp = spacy.load("en_core_med7_lg")

# this function will extract relevant entities and labels needed from medical transcription

def extract_keywords(text):
    doc = nlp(text)
    entities = []
    entities = [(ent.text, ent.label_) for ent in doc.ents]
    return entities

# Lets define our categories
surgery_keywords = ["surgery", "operation", "procedure", "acute Cholangitis", "surgisis", "appendicitis"]
cardio_pul_keywords = ["heart", "cardiovascular", "pulmonary", "lungs"]
orthopaedic_keywords = ["orthopaedic", "bone", "joint", "fracture"]
neurology_keywords = ["neurology", "nervours system", "brain", "nerve"]
general_med_keywords = ["patient", "complaining", "history", "medical"]

# This will process each medical description and check for relevant keywords
medical_doc = med['transcription']
for transcription in medical_doc:
    entities = extract_keywords(transcription.lower())

    is_surgery = any(keyword in transcription.lower() for keyword in surgery_keywords)
    is_cardio_pul = any(keyword in transcription.lower() for keyword in cardio_pul_keywords)
    is_orthopaedic = any(keyword in transcription.lower() for keyword in orthopaedic_keywords)
    is_neurology = any(keyword in transcription.lower() for keyword in neurology_keywords)
    is_general_med = any(keyword in transcription.lower() for keyword in general_med_keywords)

    print("Transcription:", transcription)
    print("Entities:", entities)
    print("Is Surgery:", is_surgery)
    print("Is Cardio Pulmonary:", is_cardio_pul)
    print("Orthopaedic:", is_orthopaedic)
    print("Neurology:", is_neurology)
    print("General Medicine:", is_general_med)
```

Transcription: HX: ,This 46y/o RHM with HTN was well until 2 weeks prior to exam when he experienced sudden onset dizziness and RUE clumsiness. The symptoms resolved within 10 min. He did well until the afternoon of admission when while moving the lawn he experienced lightheadedness, RUE dysfunction and expressive aphasia (could not get the words out). His wife took him to his local MD, and on the way there his symptoms resolved. His aphasia recurred at his physician's office and a CT scan of the brain revealed a left temporal mass. He was transferred to UIHC. PMH:, HTN for many years,MEDS:, Vasotec and Dyazide,SHX/FHX:, ETOH abuse (quit '92), 30pk-yr Cigarettes (quit '92),EXAM:, BP158/92, HR91, RR16,MS: Speech fluent without dysarthria,CN: no deficits noted,Motor: no weakness or abnormal tone noted,Sensory: no deficits noted, Coord: normal,Station: no drift,Gait ND,Reflexes: 3+ throughout. Plantars down-going bilaterally. Gen exam: unremarkable,STUDIES:, WBC14.3K, Na 132, Cl 94, CO2 22, Glucose 129. CT Brain without contrast: Calcified 2.5 x 2.5cm mass arising from left sylvian fissure/temporal lobe. MRI Brain, 8/31/92: right temporo-parietal mass with mixed signal on T1 and T2 images. It has a peripheral dark rim on T1 and T2 with surrounding edema. This suggests a component of methemoglobin and hemosiderin within it. Slight peripheral enhancement was identified. There are two smaller foci of enhancement in the posterior parietal lobe on the right. There is nonspecific white matter foci within the pons and right thalamus. Impression: right temporoparietal hemorrhage, suggesting aneurysm or mass. The two smaller foci may suggest metastasis. The white matter changes probably reflect microvascular disease. 3 Vessel cerebroangiogram, 8/31/92: Lobulated fusiform aneurysm off a peripheral branch of the left middle cerebral artery with slow flow into the vessel distal to the aneurysm. COURSE:, The aneurysm was felt to be inoperable and he was discharged home on Dilantin, ASA, and Diltiazem.
Entities: [('vasotec', 'DRUG'), ('dyazide', 'DRUG'), ('methemoglobin', 'DRUG'), ('hemosiderin', 'DRUG'), ('dilantin', 'DRUG'), ('asa', 'DRUG'), ('diltiazem', 'DRUG')]
Is Surgery: False
Is Cardio Pulmonary: False
Orthopaedic: False
Neurology: True
General Medicine: False

Transcription: CHIEF COMPLAINT:, Low back pain and right lower extremity pain. The encounter reason for today's consultation is for a second opinion regarding evaluation and treatment of the aforementioned symptoms. HPI - LUMBAR SPINE:, The patient is a male and 39 years old. The current problem began on or about 3 months ago. The symptoms were sudden in onset. According to the patient, the current problem is a result of a fall. The date of injury was 3 months ago. There is no significant history of previous spine problems. Medical attention has been obtained through the referral source. Medical testing for the current problem includes the following: no recent tests. Treatment for the current problem includes the following: activity modification, bracing, medications and work modification. The following types of medications are currently being used for the present spine problem: narcotics, non-steroidal anti-inflammatories and muscle relaxants. The following types of medications have been used in the past: steroids. In general, the current spine problem is much worse since its onset. PAST SPINE HISTORY:, Unremarkable. PRESENT LUMBAR SYMPTOMS:, Pain location: lower lumbar. The patient describes the pain as sharp. The pain ranges from none to severe. The pain is severe frequently. It is present intermittently and most of the time daily. The pain is made worse by flexion, lifting, twisting, activity, riding in a car and sitting. The pain is made better by laying in the supine position, medications, bracing and rest. Sleep alteration because of pain: wakes up after getting to sleep frequently and difficulty getting to sleep frequently. Pain distribution: the lower extremity pain is greater than the low back pain. The patient's low back pain appears to be discogenic in origin. The pain is much worse since its onset. PRESENT RIGHT LEG SYMPTOMS:, Pain location: S1 dermatome (see the Pain Diagram). The patient describes the pain as sharp. The severity of the pain ranges from none to severe. The pain is severe frequently. It is present intermittently and most of the time daily. The pain is made worse by the same things that make the low back pain worse. The pain is made better by the same things that make the low back pain better. Sleep alteration because of pain: wakes up after getting to sleep frequently and difficulty getting to sleep frequently. The patient's symptoms appear to be radicular in origin. The pain is much worse since its onset. PRESENT LEFT LEG SYMPTOMS:, None. NEUROLOGIC SIGNS/SYMPTOMS:, The patient denies any neurologic signs/symptoms. Bowel and bladder function are reported as normal.
Entities: [('narcotics', 'DRUG'), ('steroids', 'DRUG')]
Is Surgery: False
Is Cardio Pulmonary: False
Orthopaedic: False
Neurology: False
General Medicine: True

Transcription: CC: ,Delayed motor development. HX:, This 21 month old male presented for delayed motor development, "jaw quivering" and "lazy eye." He was an 8 pound 10 ounce product of a full term, uncomplicated pregnancy-labor-spontaneous vaginal delivery to a G3P3 married white female mother. There had been no known toxic intrauterine exposures. He had no serious illnesses or hospitalizations since birth. He sat independently at 7 months, stood at 11 months, crawled at 16 months, but did not cruise until 18 months. He currently cannot walk and easily falls. His gait is reportedly marked by left "intoeing." His upper extremity strength and coordination reportedly appear quite normal and he is able to feed himself, throw and transfer objects easily. He knows greater than 20 words and speaks two-word phrases. No seizures or unusual behavior were reported except for "quivering" movement of his jaw. This has occurred since birth. In addition the parents have noted transient left exotropia. PMH: ,As above. FHX:, Many family members with "lazy eye." No other neurologic diseases declared. 9 and 5 year old sisters who are healthy. SHX:, lives with parents and sisters. EXAM:, BP83/67 HR122 36.4C Head circumference 48.0cm Weight 12.68kg (70%) Height 86.0cm (70%),MS: fairly cooperative. CN: Minimal transient esotropia OS. Tremulous quivering of jaw--increased with crying. No obvious papilledema, though difficult to evaluate due to patient movement. Motor: sat independently with normal posture and no truncal ataxia. symmetric and normal strength and muscle bulk throughout. Sensory: withdrew to vibration. Coordination: unremarkable in BUE. Station: no truncal ataxia. Gait: On attempting to walk, his right foot rotated laterally at almost 70degrees. Both lower extremities could rotate outward to 90degrees. There was marked passive eversion at the ankles as well. Reflexes: 2+/2+ throughout. Musculoskeletal: pes planovalgus bilaterally. COURSE: ,CK normal. The parents decided to forego an MRI in 8/90. The patient returned 12/11/92 at age 4 years. He was ambulatory and able to run awkwardly. His general health had been good, but he showed signs developmental delay. Formal evaluation had tested his IQ at 87 at age 3.5 years. He was weakest on tasks requiring visual/motor integration and fine motor and visual discrimination skills. He was 6 months delayed in cognitive development at that time. On exam, age 4 years, he displayed mild right ankle laxity on eversion and inversion, but normal gait. The rest of the neurological exam was normal. Head circumference was 49.5cm (50%) and height and weight were in the 90th percentile. Fragile X analysis and karyotyping were unremarkable.
Entities: [('lazy', 'DRUG'), ('lazy', 'DRUG')]
Is Surgery: False
Is Cardio Pulmonary: False
Orthopaedic: False
Neurology: False
General Medicine: True