



**UNIVERSIDAD
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Doble Grado en Ingeniería Informática y Matemáticas

Trabajo Fin de Grado

**Fundamentos del Deep Learning y
desarrollo de un modelo de
Aprendizaje Federado para la
diagnosis de COVID-19 a partir de
radiografías de tórax**

Autor

Francisco Miguel Castro Macías

Tutor

Francisco Herrera Triguero

Cotutora

Siham Tabik

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To mum and dad...

Resumen

Your resumen text goes here.

Abstract

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Yo, **Francisco Miguel Castro Macías**, alumno de la titulación Doble Grado en Ingeniería Informática y Matemáticas de la **Facultad de Ciencias** y de la **Escuela Técnica Superior De Ingenierías Informática y de Telecomunicación** de la **Universidad de Granada**, con DNI XXXXXXXXX, autorizo la ubicación de la siguiente copia de mi Trabajo Fin de Grado en la biblioteca de ambos centros para que pueda ser consultada.

Granada, 3 de septiembre de 2020

F. M. Castro Macías

D. **Francisco Herrera Triguero**, Profesor del departamento de Ciencias de la Computación e Inteligencia Artificial de la Universidad de Granada.

Informa:

Que el presente trabajo, titulado ***Título***, ha sido realizado bajo su supervisión por **mi nombre**, y autorizo la defensa de dicho trabajo ante el tribunal que corresponda.

Y para que conste, expido y firmo el presente informe en Granada a 8 de julio de 2016.

profesor

Agradecimientos

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Capítulo 1

Introducción

1.1. Loquesea

Theorems can easily be defined

[`latexcompanion`]

Teorema 1.1. *Let f be a function whose derivative exists in every point, then f is a continuous function.*

Teorema 1.2 (Pythagorean theorem). *This is a theorem about right triangles and can be summarised in the next equation*

$$x^2 + y^2 = z^2$$

And a consequence of theorem 1.2 is the statement in the next corollary.

Corolario 1.3. *There's no right rectangle whose sides measure 3cm, 4cm, and 6cm.*

You can reference theorems such as 1.2 when a label is assigned.

Lema 1.4. *Given two line segments whose lengths are a and b respectively there is a real number r such that $b = ra$.*

Capítulo 2

Objetivos

A Stop on the Salt Route 1000 B.C. As they rounded a bend in the path that ran beside the river, Lara recognized the silhouette of a fig tree atop a nearby hill. The weather was hot and the days were long. The fig tree was in full leaf, but not yet bearing fruit. Soon Lara spotted other landmarks—an outcropping of limestone beside the path that had a silhouette like a man’s face, a marshy spot beside the river where the waterfowl were easily startled, a tall tree that looked like a man with his arms upraised. They were drawing near to the place where there was an island in the river. The island was a good spot to make camp. They would sleep on the island tonight. Lara had been back and forth along the river path many times in her short life. Her people had not created the path—it had always been there, like the river—but their deerskin-shod feet and the wooden wheels of their handcarts kept the path well worn. Lara’s people were salt traders, and their livelihood took them on a continual journey. At the mouth of the river, the little group of half a dozen intermingled families gathered salt from the great salt beds beside the sea. They groomed and sifted the salt and loaded it into handcarts. When the carts were full, most of the group would stay behind, taking shelter amid rocks and simple lean-tos, while a band of fifteen or so of the heartier members set out on the path that ran alongside the river. With their precious cargo of salt, the travelers crossed the coastal lowlands and traveled toward the mountains. But Lara’s people never reached the mountaintops; they traveled only as far as the foothills. Many people lived in the forests and grassy meadows of the foothills, gathered in small villages. In return for salt, these people would give Lara’s people dried meat, animal skins, cloth spun from wool, clay pots, needles and scraping tools carved from bone, and little toys made of wood. Their bartering done, Lara and her people would travel back down the river path to the sea. The cycle would begin again. It had always been like this. Lara knew no other life. She traveled back and forth, up and down the river path.

No single place was home. She liked the seaside, where there was always fish to eat, and the gentle lapping of the waves lulled her to sleep at night. She was less fond of the foothills, where the path grew steep, the nights could be cold, and views of great distances made her dizzy. She felt uneasy in the villages, and was often shy around strangers. The path itself was where she felt most at home. She loved the smell of the river on a hot day, and the croaking of frogs at night. Vines grew amid the lush foliage along the river, with berries that were good to eat. Even on the hottest day, sundown brought a cool breeze off the water, which sighed and sang amid the reeds and tall grasses. Of all the places along the path, the area they were approaching, with the island in the river, was Lara's favorite. The terrain along this stretch of the river was mostly flat, but in the immediate vicinity of the island, the land on the sunrise side was like a rumpled cloth, with hills and ridges and valleys. Among Lara's people, there was a wooden baby's crib, suitable for strapping to a cart, that had been passed down for generations. The island was shaped like that crib, longer than it was wide and pointed at the upriver end, where the flow had eroded both banks. The island was like a crib, and the group of hills on the sunrise side of the river were like old women mantled in heavy cloaks gathered to have a look at the baby in the crib—that was how Lara's father had once described the lay of the land. Larth spoke like that all the time, conjuring images of giants and monsters in the landscape. He could perceive the spirits, called numina, that dwelled in rocks and trees. Sometimes he could speak to them and hear what they had to say. The river was his oldest friend and told him where the fishing would be best. From whispers in the wind he could foretell the next day's weather. Because of such skills, Larth was the leader of the group. "We're close to the island, aren't we, Papa?" said Lara. "How did you know?" "The hills. First we start to see the hills, off to the right. The hills grow bigger. And just before we come to the island, we can see the silhouette of that fig tree up there, along the crest of that hill." "Good girl!" said Larth, proud of his daughter's memory and powers of observation. He was a strong, handsome man with flecks of gray in his black beard. His wife had borne several children, but all had died very young except Lara, the last, whom his wife had died bearing. Lara was very precious to him. Like her mother, she had golden hair. Now that she had reached the age of childbearing, Lara was beginning to display the fullness of a woman's hips and breasts. It was Larth's greatest wish that he might live to see his own grandchildren. Not every man lived that long, but Larth was hopeful. He had been healthy all his life, partly, he believed, because he had always been careful to show respect to the numina he encountered on his journeys. Respecting the numina was important. The numen of the river could suck a man under and drown him. The

numen of a tree could trip a man with its roots, or drop a rotten branch on his head. Rocks could give way underfoot, chuckling with amusement at their own treachery. Even the sky, with a roar of fury, sometimes sent down fingers of fire that could roast a man like a rabbit on a spit, or worse, leave him alive but robbed of his senses. Larth had heard that the earth itself could open and swallow a man; though he had never actually seen such a thing, he nevertheless performed a ritual each morning, asking the earth's permission before he went striding across it. "There's something so special about this place," said Lara, gazing at the sparkling river to her left and then at the rocky, tree-spotted hills ahead and to her right. "How was it made? Who made it?" Larth frowned. The question made no sense to him. A place was never made, it simply was. Small features might change over time. Uprooted by a storm, a tree might fall into the river. A boulder might decide to tumble down the hillside. The numina that animated all things went about reshaping the landscape from day to day, but the essential things never changed, and had always existed: the river, the hills, the sky, the sun, the sea, the salt beds at the mouth of the river. He was trying to think of some way to express these thoughts to Lara, when a deer, drinking at the river, was startled by their approach. The deer bolted up the brushy bank and onto the path. Instead of running to safety, the creature stood and stared at them. As clearly as if the animal had whispered aloud, Larth heard the words "Eat me." The deer was offering herself. Larth turned to shout an order, but the most skilled hunter of the group, a youth called Po, was already in motion. Po ran forward, raised the sharpened stick he always carried and hurled it whistling through the air between Larth and Lara. A heartbeat later, the spear struck the deer's breast with such force that the creature was knocked to the ground. Unable to rise, she thrashed her neck and flailed her long, slender legs. Po ran past Larth and Lara. When he reached the deer, he pulled the spear free and stabbed the creature again. The deer released a stifled noise, like a gasp, and stopped moving. There was a cheer from the group. Instead of yet another dinner of fish from the river, tonight there would be venison.

Capítulo 3

Aprendizaje Automático

De acuerdo con Tom Mitchell, el Aprendizaje Automático consiste en el estudio de algoritmos que mejoran automáticamente a través de la experiencia.

3.1. El problema del aprendizaje

Cuando decimos que un algoritmo aprende, ¿qué entendemos por aprender?

Definición. Se dice que un algoritmo o programa \mathcal{A} aprende de la experiencia E respecto a alguna tarea T y una medida de rendimiento P , si su rendimiento en la tarea T de acuerdo a P mejora con la experiencia E .

Podemos formular el problema del aprendizaje en los siguientes términos. Sean \mathcal{X}, \mathcal{Y} dos conjuntos que llamaremos espacio de entrada y de salida. Sea \mathcal{D} el conjunto de datos o ejemplos.

Queremos aproximar una función objetivo $f : \mathcal{X} \mapsto \mathcal{Y}$ de acuerdo a una medida de error $L : \mathcal{H} \mapsto \mathbb{R}$. Nuestro algoritmo \mathcal{A} usará \mathcal{D} para elegir una función $g : \mathcal{X} \mapsto \mathcal{Y}$ de un conjunto de hipótesis \mathcal{H} que aproxime a f .

La tarea T se corresponde con encontrar la función f , la experiencia E con el conjunto de datos \mathcal{D} , y la medida de rendimiento con la medida de error L .

El problema al que nos enfrentamos en este trabajo es un **problema de clasificación supervisado**. Veamos a qué nos referimos con esto.

3.1.1. Tipos de aprendizaje

En función del conjunto de datos \mathcal{D} del que aprende nuestro algoritmo encontramos dos grandes clases de aprendizaje:

- **Aprendizaje supervisado:** cada ejemplo está etiquetado con el resultado que el algoritmo debería de producir. Es decir, $\mathcal{D} \subset \mathcal{X} \times \mathcal{Y}$ y se busca encontrar una relación entre la etiqueta y el ejemplo.
- **Aprendizaje no supervisado:** los datos no están etiquetados. Ahora $\mathcal{D} \subset \mathcal{X}$ y pretendemos identificar propiedades de la estructura del conjunto de datos.

3.1.2. Problema de clasificación

El aprendizaje automático puede aplicarse para resolver multitud de problemas: clasificación, regresión, predicción de series temporales, detección de anomalías, generación de nuevos datos, etc.

En un problema de clasificación el espacio de salida consiste en una serie de categorías o clases y queremos que nuestro algoritmo asigne a cada ejemplo una clase de forma correcta. Es decir, $\mathcal{Y} = \{1, \dots, C\}$ con $C \in \mathbb{N}$. Si $C = 2$, tenemos un problema de clasificación binaria.

De ahora en adelante, nos centraremos en el aprendizaje supervisado. Concretamente, hablaremos de problemas de clasificación.

3.2. Factibilidad del aprendizaje

El algoritmo de aprendizaje usa el conjunto de entrenamiento \mathcal{D} , que en la práctica será un conjunto finito de ejemplos, para aprender la función objetivo. ¿Por qué un conjunto limitado de datos puede revelar información suficiente para lograr nuestro objetivo? Para responder a esta pregunta tendremos que añadir algunas hipótesis adicionales a la formulación del problema. Escribamos $\mathcal{D} = \{(x_1, y_1), \dots, (x_N, y_N)\}$ y supongamos:

H1. Tras fijar el espacio \mathcal{H} , los ejemplos x_1, \dots, x_N han sido extraídos de forma independiente de acuerdo a una distribución de probabilidad P sobre el espacio de entrada \mathcal{X} .

La función objetivo f es completamente desconocida. Lo que obtenemos como resultado del aprendizaje es una función g que aproxima a f . Para medir cómo de buena es esta aproximación, recurrimos a la función de pérdida ℓ . En la situación más general, tendremos una función $\ell : \mathcal{Y} \times \mathcal{Y} \mapsto \mathbb{R}$, tal que $\ell(u, v)$ mide el error que cometemos al asignar a un ejemplo la etiqueta u cuando su etiqueta correcta es v .

Definimos

$$L(h) = \mathbb{E}_{X \sim P}[\ell(h(X), f(X))] \quad \forall h \in \mathcal{H}$$

y queremos resolver:

$$\text{Encontrar } g \in \mathcal{H} \text{ tal que } L(g) = \min_{h \in \mathcal{H}} L(h)$$

No tenemos acceso a la función f ni tampoco a la distribución P . Por tanto, resolver el anterior problema será inviable en la mayor parte de las situaciones. Una forma natural de proceder es definir

$$L_{in}(h, \mathcal{D}) = \frac{1}{N} \sum_{(x_n, y_n) \in \mathcal{D}} \ell(h(x_n), y_n) \quad \forall h \in \mathcal{H}$$

y, una vez fijado \mathcal{D} , minimizar L_{in} en lugar de L . Lo que vamos a probar es que reducir L_{in} conlleva reducir L , luego podemos aspirar a soluciones subóptimas.

Para un problema de clasificación, definimos $\ell(u, v) = 1$ si $u \neq v$ y 0 si $u = v$. Vamos a omitir la dependencia de \mathcal{D} al escribir L_{in} y vamos a llamar $L_{out} = L(h) = P[h(x) \neq f(x)] \quad \forall h \in \mathcal{H}$. Vamos a usar la desigualdad de Hoeffding:

Lema 3.1 (Desigualdad de Hoeffding). *Sea Z_1, \dots, Z_N una muestra aleatoria simple de una variable aleatoria Z que sigue una distribución de Bernoulli con media $E[Z]$. Sea \bar{Z} la media muestral. Sea ϵ un número real estrictamente positivo. Entonces se cumple que:*

$$P[|E[Z] - \bar{Z}| > \epsilon] \leq 2e^{-2\epsilon^2 N} \quad (3.1)$$

Supongamos primero que $\mathcal{H} = \{h\}$. Definamos $I : \mathcal{X} \mapsto \{0, 1\}$ como $I(x) = 1$ si $h(x) \neq f(x)$ y $I(x) = 0$ si $h(x) = f(x)$. Tenemos entonces que I es una variable aleatoria que sigue una distribución de Bernoulli, cuya esperanza se corresponde con L_{out} . Si escribimos $I_n = \ell(x_n, y_n)$, tenemos que I_1, \dots, I_n es una muestra aleatoria simple de I , y podemos aplicar (3.1) para un $\epsilon > 0$ fijo obteniendo que:

$$P[|L_{out}(h) - L_{in}(h)| > \epsilon] \leq 2e^{-2\epsilon^2 N}$$

Esta desigualdad nos dice que, fijado un margen de error ϵ , la diferencia entre L_{in} y L_{out} queda controlada por el tamaño de la muestra. Aumentando el tamaño de N , la probabilidad de exceder el margen de error tiende a cero. Ahora supongamos que $\mathcal{H} = \{h_1, \dots, h_M\}$. Denotemos por g la solución aproximada que obtiene el

algoritmo \mathcal{A} . Denotemos por \mathbb{B} el evento $|L_{out}(g) - L_{in}(g)| > \epsilon$ y para cada h_m , por \mathbb{B}_m el evento $|L_{out}(h_m) - L_{in}(h_m)| > \epsilon$. Se cumple que $\mathbb{B} = \bigcup_{m=1}^M \mathbb{B}_m$.

3.3. Optimización: gradiente descendente

Capítulo 4

Deep Learning

4.1. Introduction

Capítulo 5

Aprendizaje Federado

Apéndice A

Appendix Title