Next-Gen Well Logs: Data Standards, QC, and ML-Augmented Petrophysics

A Practical Guide for Subsurface Professionals

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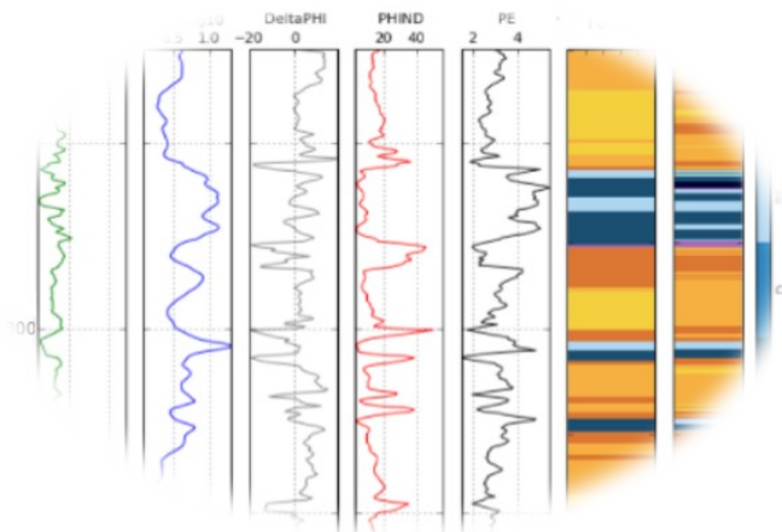
Current Version: 2.0 (January 2026)
First Published: October 2025



Revision History

Version	Date	Description of Changes
1.0	Oct 2025	**Initial Release:** Introduced as a practical, technically grounded guide for early-career professionals in the upstream energy domain. Established a foundational understanding of digital well log data standards (LAS 2.0, DLIS, LIS, BIT, and SEGY), best practices for data conditioning and quality control (QC), and step-by-step guidance on machine learning (ML)-augmented petrophysical workflows.
2.0	Jan 2026	**Expanded and Enhanced Edition:** • Added a new chapter on Data Engineering Basics with Linux and SQL tools, along with GenAI-assisted workflows for subsurface reports. • Added new appendices: OSDU Explained – What Upstream Oil & Gas Teams Need to know and Essential Python Libraries for Well Log Data and ML Workflows. **Technical Updates:** • Released in PDF/UA (Universal Accessibility)-compliant format to support inclusive access. • Introduced data cleansing workflows addressing non-printable ("Invisible Man") characters in spreadsheet datasets and DLIS file content verification. • Added a new ML-assisted petrophysical workflow for scalable porosity prediction using conventional logs across multi-well field datasets.

Preface

"To the logging field engineers, vigilant data stewards, and all subsurface professionals: your tireless efforts in shaping, refining, and safeguarding the integrity of well log data form the quiet force behind clarity and insight. Through your devotion, the hidden truths of the earth are revealed, guiding reservoirs, wells, and the onward march of digital transformation. For this steadfast dedication, I extend my deepest gratitude."

Welcome to this e-book, crafted to connect field-proven logging practices with modern, data-driven workflows transforming subsurface operations. As data volumes and complexity continue to grow, mastering digital standards and AI-assisted techniques has become essential for achieving accuracy, efficiency, and insight in petrophysical analysis.

This e-book serves as a practical, technically grounded guide for early-career professionals in the upstream energy domain; logging engineers, geoscientists, petrophysicists, petroleum engineers, and subsurface data specialists. Its primary goal is to build a strong foundation in digital well log data standards (LAS, DLIS, LIS, BIT, and SEGY), introduce best practices for data conditioning and quality control, and provide step-by-step examples of machine learning (ML)-augmented petrophysical workflows.

Through real-world Python tools and use cases, readers will learn how to prepare, validate, and analyze well log data to support petrophysical interpretation and reservoir modeling in a modern, data-driven environment. By combining domain expertise with digital proficiency, this guide encourages readers to approach data with both technical rigor and creative insight.

Ultimately, this e-book aims to empower the next generation of subsurface professionals with the knowledge, tools, and confidence to deploy ML-enabled solutions that enhance quality, consistency, and interpretation across the petrophysical workflow. I wish you an insightful journey through these pages and extend my sincere thanks for your dedication and curiosity.

Special thanks, with deepest gratitude to those who light my path: my beloved wife, Susie; our daughters, Aji, Aja, and JJ; and to my parents, brothers and sisters, whose love and courageous hearts have been the quiet strength behind every step of this journey.

What's New in This Edition

This second edition represents a measured evolution of the first, shaped by practical experience, constructive reader feedback, and the evolving demands of subsurface data work. The positive response to the initial release provided both validation and motivation to expand the scope, refine the technical focus, and enhance the practical relevance of the material– while preserving its original intent.

New Chapter: Data Engineering with Linux and SQL, and GenAI-Assisted Workflows

This edition introduces a new chapter on data engineering fundamentals for subsurface data, with a focus on Linux and SQL-based workflows that enable scalable, traceable, and reliable data preparation. It also presents GenAI-assisted workflows for subsurface reports, demonstrating how generative AI can enhance efficiency and clarity by augmenting traditional data handling tasks–particularly when working with unstructured subsurface reports.

Inclusive and Accessible Publication

This edition is published in a PDF/UA (Universal Accessibility)–compliant format to support inclusive access. It ensures compatibility with assistive technologies and reflects the author's commitment to equitable knowledge sharing.

Strengthened Data Quality and Verification Practices

Several technical enhancements have been incorporated to reinforce data integrity, including:

- **Data cleansing workflows** to detect and remove non-printable **"**Invisible Man" characters commonly found in spreadsheet-based datasets
- **DLIS file content verification** to ensure structural and metadata consistency prior to downstream use

These additions reflect a continued emphasis on disciplined preparation as the foundation for dependable and reproducible subsurface interpretation.

A New ML Workflow for Field-Scale Application

A new machine learning workflow for scalable porosity prediction has been added, using conventional well logs (GR, RHOB, NPHI, RT, and DT). Designed for multi-well, field-scale datasets, this workflow emphasizes reproducibility, consistency, and alignment with established petrophysical principles.

These updates do not alter the spirit of the work; they refine its execution. Informed by reader feedback and field experience, this edition continues to provide practical, disciplined guidance for subsurface professionals seeking clarity, consistency, and confidence in a data-driven environment.

New Appendices:

OSDU Explained–What Upstream Oil & Gas Teams Need to Know

This edition adds a new appendix introducing the Open Subsurface Data Universe (OSDU), an open, standards-based data platform developed under The Open Group for the upstream energy industry. It outlines how OSDU provides a technology-agnostic, cloud-ready foundation for governing, integrating, and scaling subsurface data to support modern analytics and AI-enabled workflows.

Common Python Libraries for Well Log Data and ML Workflows. This section highlights six widely used Python libraries for digital well log processing, data quality control, and ML-augmented petrophysical workflows. These libraries are valued in the energy industry for their reliability, versatility, and strong open-source support.

Code Repository

For all Python scripts and code examples featured in this e-book, please visit my GitHub portfolio: *github.com/edirnandi/petrophysical-qc*

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A Practical Overview of Digital Well Log Data Standards

1. Introduction

Digital well log data forms the foundation for subsurface evaluation, reservoir characterization, and well performance analysis in the upstream oil and gas industry. Over the decades, several data standards have been developed to ensure consistency, interoperability, and reliability in the storage and exchange of logging data.

This guide provides an overview of the key digital well log data standards— **LAS 2.0**, **DLIS (API RP66)**, **LIS**, **BIT**, and **SEGY**. It is designed for junior geoscientists, petrophysicists, petroleum engineers and data specialists who need a clear understanding of how these formats are structured, their primary applications, and how they fit within modern data management platform and workflows.

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2. LAS 2.0 Specification and Compliance

The **Log ASCII Standard (LAS)** is a widely adopted text-based format developed by the **Canadian Well Logging Society (CWLS)** for storing and exchanging digital well log data. Introduced in 1989, LAS 2.0 (released in 1992) addressed inconsistencies from earlier versions. While LAS 3.0 (1999) expanded storage capabilities, LAS 2.0 remains dominant for its simplicity and broad software support.

LAS 2.0 Structure

LAS 2.0 files are divided into structured sections:

1. **~VERSION INFORMATION** – Identifies the LAS version and wrapping type (WRAP/NO-WRAP).
    - VERS.: LAS version (e.g., 2.0)
    - WRAP: Indicates line wrapping (YES or NO).
2. **~WELL INFORMATION** – Metadata about the well, including depth range and null values.
    - STRT.: Start depth

   - STOP.: Stop depth
   - STEP.: Step size
   - NULL.: Missing value indicator
3. **~CURVE INFORMATION** – Describes the log curves with mnemonic, unit, and description.
   - Example: GR.API : Gamma Ray
4. **~PARAMETER INFORMATION** – Lists additional logging parameters.
5. **~ASCII LOG DATA** – Contains the actual numeric log values.

Compliance with LAS 2.0 ensures interoperability across diverse software systems used for petrophysical interpretation and data management.

LAS File Formats

- **WRAP (Multiple Lines per Depth Step)**: Allows more detailed data per interval.
- **NO-WRAP (One Line per Depth Step)**: Simpler format; each depth step is one record.
- **LAS 2.0 Sample**

```
~VERSION INFORMATION
VERS. 2.0 : CWLS LOG ASCII STANDARD - VERSION 2.0
WRAP. NO : ONE LINE PER DEPTH STEP

~WELL INFORMATION
#MNEM.UNIT      DATA            DESCRIPTION
STRT.M          100.0           START DEPTH
STOP.M          140.0           STOP DEPTH
NULL.           -999.25         NULL VALUE
WELL.           WELL-1          WELL NAME

~CURVE INFORMATION
#MNEM.UNIT      DESCRIPTION
DEPT.M          DEPTH
GR.API          GAMMA RAY
~A
100.0  45.5
110.0  46.0
120.0  46.7
130.0  96.7
140.0  47.3
```

Reference

1) Canadian Well Logging Society: LAS (Log ASCII Standard)
2) US Geological Survey: Log ASCII Standard (LAS) files for geophysical wireline well logs and their application to geologic cross sections through the central Appalachian basin

3. DLIS (Digital Log Interchange Standard / API RP66)

The **Digital Log Interchange Standard (DLIS)**, defined in **API Recommended Practice 66**, was introduced to overcome the limitations of earlier binary formats like LIS and BIT. It supports complex data structures, metadata organization, and dynamic sampling rates—making it ideal for modern wireline and logging-while-drilling data.

Key Features

- **Robust Data Identification**: Each data item is uniquely identified.
- **Complex Data Representation**: Handles arrays, strings, and multi-channel datasets.
- **Dynamic Channel Support**: Allows multiple frame types and sampling rates within a single file.

Data Organization

DLIS uses two hierarchical levels: - **Logical Format**: Organizes data into logical records and files, representing self-contained measurement datasets. - **Physical Format**: Defines how logical records are stored on physical media such as magnetic tape or disk.

DLIS ensures data can be accurately exchanged across systems, independent of acquisition equipment.

Reference: RP66/DLIS V1 Specification

4. LIS (Log Information Standard)

The **LIS** format, developed by **Schlumberger** in the early 1970s, was among the first attempts to standardize digital well log data. It groups data by type in logical records—**INFORMATION** (metadata) and **DATA** (measurements). Both are essential to reconstruct a complete digital service.

Characteristics

- **Dictionary-Controlled Mnemonics** define record attributes such as name, size, unit, and representation code.
- **Flexible Implementation**: Variations exist across contractors, which sometimes impairs decoding.
- **Limitations**: Short mnemonic length (max. 4 characters) and limited flexibility compared to DLIS.

Occasionally, LIS tapes converted from DLIS may exhibit inconsistencies (e.g., curve name truncation), requiring careful handling during import into modern databases.

Reference: LIS 79 Description Reference Manual

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5. BIT (Basic Information Tape)

The **BIT** format, introduced by **Atlas Wireline Services** in the 1970s, was designed for recording basic log data on magnetic tape. Each tape consists of sequential, unblocked records separated by inter-record gaps (IRGs).

Structure

- **General Heading Record**: Contains well identification and processing parameters.
- **Data Records**: Store actual measurement values.

A BIT tape may include up to 20 curves, with each file beginning with a heading record followed by multiple data records. The format is simple but limited in scalability and metadata richness compared to LIS or DLIS.

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6. SEGY (Standard for Exchange of Seismic Data)

The **SEGY** (or SEG Y) format, established by the **Society of Exploration Geophysicists (SEG)** in 1975 and updated in 2002 (Rev 1.0) and 2017 (Rev 2.0), is the industry standard for **seismic and borehole seismic (VSP)** data exchange.

Structure

1. **Textual Header (3200 bytes)** – Human-readable survey and acquisition information.

2. **Binary Header (400 bytes)** – File-level parameters like sample rate and format code.
3. **Trace Headers** – Contain metadata for each trace (e.g., depth, channel, coordinates).
4. **Trace Data** – Actual seismic samples (16-, 32-, or 64-bit values).

Applications

Commonly used for; Checkshot and zero-offset VSPs, Offset and walkaway VSPs, and Crosswell seismic data.

Advantages

- Universally supported by seismic software.
- Flexible structure with extended trace headers (Rev 2.0).
- Integrates easily with LAS and DLIS for combined well-seismic analysis.

References: SEG-Y_r2.0 - SEG Technical Standards Committee 2017

7. Summary Comparison of Digital Log Data Standards

Format	Origin / Year	Data Type	Structure	Advantages	Limitations
LAS 2.0	CWLS, 1992	ASCII Well Logs	Sectioned text format (~VERSION, ~WELL, ~CURVE, ~DATA)	Simple, human-readable, widely supported	Limited metadata, less suited for complex datasets
DLIS	API RP66, 1991	Binary Well Logs	Logical and physical structures	Rich metadata, dynamic channels, standardized	Complex decoding, larger file size
LIS	Schlumberger, 1970s	Binary Well Logs	INFORMATION & DATA records	Historical standard, flexible	Proprietary variations, short mnemonics
BIT	Atlas, 1970s	Binary Well Logs	Header + Data records	Simple and lightweight	Minimal metadata, legacy format

Format	Origin / Year	Data Type	Structure	Advantages	Limitations
SEGY	SEG, 1975 (Rev. 2017)	Seismic / VSP Data	Header + Trace + Binary blocks	Universal seismic standard, integrates with logs	Large file size, limited log metadata

8. Conclusion

Understanding these digital log data standards is essential for any professional involved in subsurface data management or analysis and interpretation. **LAS** remains the most common for well logs, **DLIS** offers the most comprehensive data model, **LIS** and **BIT** are legacy but still encountered, and **SEGY** bridges the well and seismic domains through VSP and borehole seismic applications.

As data integration and digitalization accelerate in the energy sector, familiarity with these standards enables seamless interoperability, efficient QC, and more robust geoscience workflows-- key skills for the next generation of data-savvy geoscientists and engineers.

Digital Log Data Preparation and Editing: A Practical Guide for Petrophysical Analysis

1. Introduction

Digital well log data serve as the foundation for petrophysical interpretation, reservoir characterization, and data-driven analysis. The most common formats, LAS (Log ASCII Standard) and DLIS (Digital Log Interchange Standard), were developed under the Canadian Well Logging Society (CWLS) and the American Petroleum Institute (API) RP 66 respectively. Ensuring data quality and readiness is essential before loading and validating data in petrophysical software such as Techlog, or IP, or in modern data platforms like Open Subsurface Data Universe (OSDU– A brief overview of OSDU and its relevance to modern subsurface data workflows is provided in Appendix A). This includes verifying conformity to format specifications, using standardized null values and date formats, maintaining consistent depth intervals, and ensuring valid metadata. Studies show that poor data quality can increase project costs by 15–25% and consume up to 50% of project time resolving inefficiencies (Source: US Geological Survey [USGS] and Society of Petroleum Engineers [SPE]).

This document provides both automated and manual workflows using Python utilities and lightweight Hexadecimal (Hex) editor tools for practical, field-level data preparation.

2. Digital Log Validation and Quality Control

Validation ensures that well log files conform to their technical standards and contain the necessary sections for analysis. Python-based validators using the LASIO and DLISIO libraries provide an open-source, reproducible approach to QC.

2.1 LAS Validator

The LAS Validator checks for CWLS LAS 2.0 conformity. It verifies headers (~V, ~W, ~C, ~A), WRAP mode, null values, and consistency between declared START/STOP depths and actual data. The script supports multi-file batch validation and outputs a CSV summary.

```
# LASValidatorv2-free.py
```

```
import pandas as pd
import os
import lasio
from tkinter import Tk, filedialog
from datetime import datetime
```

```
# Step 1: Verify LAS 2.0 Conformity
def verify_las_file(las_file, tolerance=1e-3):
    try:
        las = lasio.read(las_file, ignore_header_errors=True)
        sections = [section.upper() for section in las.sections.keys()]
        errors = []

        # Check mandatory sections
        required_sections = ['VERSION', 'WELL', 'CURVES']
        for req in required_sections:
            if req not in sections:
                errors.append(f"Missing section: {req}")

        # Check version
        try:
            version = float(str(las.version['VERS'].value).strip())
            if version != 2.0:
                errors.append(f"Invalid version: {version} (Expected 2.0)")
        except Exception:
            errors.append("Missing or invalid VERSION information")

        # Check WRAP mode
        try:
            wrap_mode = str(las.version['WRAP'].value).strip().upper()
            if wrap_mode not in ['YES', 'NO']:
                errors.append(f"Invalid WRAP mode: {wrap_mode}")
        except Exception:
            errors.append("Missing WRAP mode in VERSION section")

        # Check first curve is DEPT, DEPTH, TIME, or INDEX
        try:
            first_curve = las.curves[0].mnemonic.strip().upper()
            if first_curve not in ['DEPT', 'DEPTH', 'TIME', 'INDEX']:
                errors.append(f"Invalid index curve: {first_curve}")
        except Exception:
            errors.append("Missing or invalid CURVE information")

        # Check NULL values
        if 'NULL' not in las.well:
            errors.append("Missing NULL value in WELL section")

        # Check WELL ID is present (UWI or WELL only)
        well_id_present = any(mnemonic.upper() in ['UWI', 'WELL'] for
mnemonic in las.well.keys())
        if not well_id_present:
```

```
            errors.append("Missing Well ID in WELL section (UWI or WELL)")

        # Check START and STOP consistency with tolerance
        try:
            # Possible keys to look for
            start_keys = ['STRT', 'START', 'STRT.M', 'START.M', 'STRT.F',
'START.F']
            stop_keys  = ['STOP', 'STOP.M', 'STOP.F']

            # Find actual keys present in LAS well section
            well_keys = {k.upper(): k for k in las.well.keys()}

            found_pairs = []
            for sk in start_keys:
                for ek in stop_keys:
                    # Match STRT with STOP (same suffix if present)
                    if sk.replace("START", "STOP") == ek or
sk.replace("STRT", "STOP") == ek:
                        if sk in well_keys and ek in well_keys:
                            found_pairs.append((well_keys[sk],
well_keys[ek]))

            if not found_pairs:
                errors.append("Missing START/STOP pair in WELL section")
            else:
                data_start = float(las.index[0])
                data_stop = float(las.index[-1])

                for sk, ek in found_pairs:
                    header_start = float(str(las.well[sk].value).strip())
                    header_stop = float(str(las.well[ek].value).strip())

                    if abs(header_start - data_start) > tolerance:
                        errors.append(
                            f"Mismatch START ({sk}): Header={header_start},
Data={data_start} "
                            f"(Diff={abs(header_start - data_start):.6f} >
Tolerance={tolerance})"
                        )
                    if abs(header_stop - data_stop) > tolerance:
                        errors.append(
                            f"Mismatch STOP ({ek}): Header={header_stop},
Data={data_stop} "
                            f"(Diff={abs(header_stop - data_stop):.6f} >
Tolerance={tolerance})"
                        )
        except Exception:
            errors.append("Error validating START/STOP consistency in WELL
section or data")

        return "Valid" if not errors else ", ".join(errors)


    except Exception as e:
```

```
        return f"Error reading file: {e}"


# Step 2: Interactive File Selection and Verification
def main():
    # Initialize file dialog
    Tk().withdraw()  # Hide the root window
    file_paths = filedialog.askopenfilenames(title="Select LAS Files",
filetypes=[("LAS files", "*.las")])

    if not file_paths:
        print("No files selected.")
        return

    # Verify each file
    results = []
    for file in file_paths:
        status = verify_las_file(file)
        results.append({"File": os.path.basename(file), "Status": status})
        print(f"{os.path.basename(file)}: {status}")

    # Save results to timestamped CSV
    output_df = pd.DataFrame(results)
    timestamp = datetime.now().strftime("%Y%m%d_%H%M%S")
    output_file = f"las_verification_results_{timestamp}.csv"
    output_df.to_csv(output_file, index=False)
    print(f"Results saved to {output_file}")


if __name__ == "__main__":
    main()
```

This validator is a foundational QC tool that can be integrated into data pipelines or pre-ingestion steps in well log repositories.

2.2 DLIS Validator

The DLIS Validator validates binary DLIS files according to API RP 66 specification. It checks logical file structures, frames, and channels to confirm completeness. This script relies on the DLISIO library, which is widely adopted in digital subsurface workflows.

```
# DLISCheck-free.py
import os
import pandas as pd
from tkinter import Tk, filedialog
from dlisio import dlis
from pathlib import Path

def validate_dlis_file(dlis_file):
    """
```

```
    Validate a DLIS file for conformity to the DLIS/API RP66 standard using
both physical and logical file checks.

    Parameters:
    dlis_file (str): The file path of the DLIS file to be validated.
    Returns:
    str: A message indicating the validation result.
    """
    try:
        # Ensure the file exists
        if not os.path.isfile(dlis_file):
            return f"Error: {dlis_file} is not a valid file or does not
exist."

        # Load the DLIS file
        physical_file = dlis.load(dlis_file)
        if not physical_file:
            return "File is empty or not a valid DLIS file."

        # Describe the physical file
        description = physical_file.describe()
        print(description)

        # Logical file validation
        logical_file_issues = []
        for logical_file in physical_file:
            # Check logical file metadata
            if not logical_file.origins:
                logical_file_issues.append("Logical file missing origin
metadata.")

            # Validate channels
            for channel in logical_file.channels:
                if not channel.name:
                    logical_file_issues.append("Channel with missing name
found.")

            # Validate frames
            for frame in logical_file.frames:
                if not frame.name:
                    logical_file_issues.append("Frame with missing name
found.")

        if logical_file_issues:
            return "Logical file issues detected: " + ";
".join(logical_file_issues)

        return "DLIS file conforms to the standard."

    except dlis.DlisError as e:
        return f"DLIS-specific error: {e}"
    except Exception as e:
        return f"Error processing file: {e}"
```

```
def main():
    # Initialize Tkinter window (hidden)
    Tk().withdraw()

    # Select a folder containing DLIS files
    folder_path = filedialog.askdirectory(title="Select Folder Containing
DLIS Files")

    if not folder_path:
        print("No folder selected.")
        return

    folder_path = Path(folder_path).resolve()
    dlist_files = [str(folder_path / f) for f in os.listdir(folder_path) if
f.lower().endswith('.dlis')]

    if not dlist_files:
        print("No DLIS files found in the selected folder.")
        return

    # Verify each DLIS file
    results = []
    for file in dlist_files:
        status = validate_dlis_file(file)
        results.append({"File": os.path.basename(file), "Status": status})
        print(f"{os.path.basename(file)}: {status}")

    # Save results to CSV
    output_df = pd.DataFrame(results)
    output_file = "dlis_verification_results.csv"
    output_df.to_csv(output_file, index=False)
    print(f"Results saved to {output_file}")

if __name__ == "__main__":
    main()
```

2.3 DLIS Log parameters extractor

Raw log data–often called original or field data–is acquired once at the wellsite and can never be exactly reproduced. In contrast, derived or processed logs are created from the raw dataset and therefore contain interpretive elements, meaning multiple processed versions can exist. Most historical raw logs are delivered in DLIS or LIS formats—both binary. Today, DLIS remains widely used because it retains richer contextual information (origins, tool strings, parameters, acquisition settings), while LAS files are text-based and usually include limited metadata.

To support early-stage quality control–particularly when petrophysical software such as Techlog or IP is not accessible–this practical utility, DLIS_header_to_excel, can be used.

It automatically extracts key DLIS metadata, including log parameters, tools, channels, and units, into an Excel file for efficient and rapid validation.

DLIS_header_to_excel.py

```
# dlis_header_to_excel.py
#
# DLIS header-only extractor (Tkinter + dlisio),generate separate Excel files
per DLIS file.
#
#
--------------------------------------------------------------------------------
---------
import os
import pandas as pd
import numpy as np
from tkinter import Tk, filedialog, messagebox
from dlisio import dlis

# --------------------------------------------------
# Helpers
# --------------------------------------------------

def normalize_scalar(val):
    if val is None:
        return None
    if isinstance(val, (str, int, float, bool)):
        return val
    return str(val)

def first_attr(obj, names, default=None):
    for n in names:
        if hasattr(obj, n):
            try:
                v = getattr(obj, n)
                return v() if callable(v) else v
            except:
                continue
    return default


# --------------------------------------------------
# Vendor-specific unwrapping
# --------------------------------------------------

def unwrap_vendor_specific(param):
    # Schlumberger
    slb_fields = [
        "value", "v", "val", "scalar", "scalars",
        "data", "elements", "contents",
        "text", "enum", "values"
    ]
    for f in slb_fields:
        if hasattr(param, f):
```

```
            try:
                v = getattr(param, f)
                if callable(v): v = v()
                if v not in [None, ""]:
                    return v
            except:
                pass

    # Halliburton
    hal_fields = ["getvalue", "representation_code", "array"]
    for f in hal_fields:
        if hasattr(param, f):
            try:
                v = getattr(param, f)
                v = v() if callable(v) else v
                if v not in [None, ""]:
                    return v
            except:
                pass

    # Baker / INTEQ
    baker_fields = ["data", "values", "elements"]
    for f in baker_fields:
        if hasattr(param, f):
            try:
                v = getattr(param, f)
                v = v() if callable(v) else v
                if v not in [None, ""]:
                    return v
            except:
                pass

    return None


def unwrap_param_value(param):
    try_val = unwrap_vendor_specific(param)
    if try_val not in [None, ""]:
        val = try_val
    else:
        try:
            val = param.getvalue() if hasattr(param, "getvalue") else
getattr(param, "value", None)
        except:
            val = None

    # Recursive peeling
    seen = set()
    while True:
        if id(val) in seen:
            break
        seen.add(id(val))

        next_val = None
```

```
        if hasattr(val, "getvalue"):
            try: next_val = val.getvalue()
            except: pass
        elif hasattr(val, "value"):
            try: next_val = val.value
            except: pass

        if next_val is None or next_val is val:
            break
        val = next_val

    # data_array → numpy array
    if hasattr(val, "array"):
        try: val = val.array
        except: pass

    # array → CSV string
    if isinstance(val, (np.ndarray, list, tuple)):
        try: return ", ".join(str(v) for v in val)
        except: return str(val)

    return val if val is not None else str(param)


# --------------------------------------------------
# Extraction per file
# --------------------------------------------------

def extract_dlis_header(dlis_file):
    try:
        pf = dlis.load(dlis_file)
    except Exception as e:
        print(f"❌ Cannot load {dlis_file}: {e}")
        return None

    origins, params, tools, channels, frames, chinfo = [], [], [], [], [], []

    for lf_index, lf in enumerate(pf):
        lf_id = lf_index + 1

        # -------- Origins --------
        for o in lf.origins:
            try:
                d = {k: normalize_scalar(v) for k, v in o.describe().items()}
            except:
                d = {"repr": str(o)}
            d["LogicalFile"] = lf_id
            origins.append(d)

        # -------- Parameters --------
        for p in lf.parameters:
            name = first_attr(p, ["objname", "name", "tag", "mnemonic",
"id"])
            value = unwrap_param_value(p)
```

```
            params.append({
                "LogicalFile": lf_id,
                "Name": normalize_scalar(name),
                "Value": normalize_scalar(value),
                "Raw": str(p)
            })

        # -------- Tools --------
        for t in lf.tools:
            name = first_attr(t, ["objname", "name", "toolname", "id"])
            try:
                d = {k: normalize_scalar(v) for k, v in t.describe().items()}
            except:
                d = {"repr": str(t)}
            tools.append({
                "LogicalFile": lf_id,
                "ToolName": normalize_scalar(name),
                "Description": str(d)
            })

        # -------- Channels & Channel Info --------
        for ch in lf.channels:
            chname = first_attr(ch, ["name", "mnemonic", "objname"])
            channels.append({
                "LogicalFile": lf_id,
                "ChannelName": normalize_scalar(chname),
                "Raw": str(ch)
            })

            # Mnemonic-Unit-Description table
            mnemonic = first_attr(ch, ["mnemonic", "name"])
            unit = first_attr(ch, ["unit", "units"])
            try:
                desc = ch.describe()
                long_name = desc.get("long_name", None)
            except:
                long_name = None

            chinfo.append({
                "LogicalFile": lf_id,
                "Mnemonic": normalize_scalar(mnemonic),
                "Unit": normalize_scalar(unit),
                "Description": normalize_scalar(long_name)
            })

        # -------- Frames --------
        for fr in lf.frames:
            fname = first_attr(fr, ["name", "objname", "tag", "identifier"])
            frames.append({
                "LogicalFile": lf_id,
                "FrameName": normalize_scalar(fname),
                "Raw": str(fr)
            })
```

```
    return (
        pd.DataFrame(origins),
        pd.DataFrame(params),
        pd.DataFrame(tools),
        pd.DataFrame(channels),
        pd.DataFrame(frames),
        pd.DataFrame(chinfo)
    )


# ----------------------------------------------------
# Tkinter UI
# ----------------------------------------------------

def main():
    Tk().withdraw()

    files = filedialog.askopenfilenames(
        title="Select DLIS file(s)",
        filetypes=[("DLIS files", "*.dlis"), ("All files", "*.*")]
    )
    if not files:
        print("No files selected.")
        return

    outdir = "output_dlis_header"
    os.makedirs(outdir, exist_ok=True)

    for f in files:
        print(f"\n→ Processing {f}")
        result = extract_dlis_header(f)
        if result is None:
            continue

        df_o, df_p, df_t, df_c, df_f, df_ci = result

        # Deduplicate ChannelInfo only
        df_ci = df_ci.drop_duplicates(subset=["Mnemonic", "Unit",
"Description"])

        # Write individual Excel file
        basename = os.path.splitext(os.path.basename(f))[0]
        excel_path = os.path.join(outdir, f"{basename}_header.xlsx")

        with pd.ExcelWriter(excel_path, engine="openpyxl") as x:
            df_o.to_excel(x, "Origins", index=False)
            df_p.to_excel(x, "Parameters", index=False)
            df_t.to_excel(x, "Tools", index=False)
            df_c.to_excel(x, "Channels", index=False)     # unchanged
            df_f.to_excel(x, "Frames", index=False)
            df_ci.to_excel(x, "ChannelInfo", index=False) # deduped

        print(f"✔ Saved: {excel_path}")
```

```
    # Popup when all files are done
    messagebox.showinfo("DLIS Header Extractor", "Finished! Excel files have
been generated.")
    print("\nDone.\n")


if __name__ == "__main__":
    main()
```

3. Data Wrangling and Preparation

Data wrangling involves transforming, standardizing, and conditioning log datasets before analysis. The following Python utilities simplify key steps: format conversion, log header extraction, and null values standardization.

3.1 ASCII to LAS 2.0 Conversion (ascii2las)

Many legacy log datasets exist in tabular ASCII (CSV/TXT) form. Converting these to LAS 2.0 improves interoperability. This script generates a CWLS-compliant LAS with standardized headers and units.

```
# ascii2las.py - Convert ASCII logs into CWLS LAS 2.0

import pandas as pd
from tkinter import Tk, filedialog
import os

# --- Constants for LAS 2.0 header (Curve units taken  from SLB curve
mnemonic dictionary https://www.apps.slb.com/cmd/) ---
CURVE_INFO = [
    ("DEPT", "M", "Depth (m)"),
    ("GR", "GAPI", "Gamma Ray (API units)"),
    ("RES", "OHM.M", "Resistivity (ohm·m)"),
    ("RHOB", "G/CM3", "Bulk Density (g/cm³)"),
    ("NPHI", "NAPI", "Neutron Porosity (nAPI)"),
    ("DT", "US/FT", "Sonic Transit Time (µs/ft)")
]

# --- File dialog to pick CSV, TXT or Excel file ---
def select_file():
    root = Tk()
    root.withdraw()  # Hide the main window
    file_path = filedialog.askopenfilename(
        title="Select a CSV, TXT, or Excel File",
        filetypes=[("Data files", "*.csv *.txt *.xls *.xlsx")]
    )
    return file_path

# --- Read the file into a pandas DataFrame ---
def read_data(file_path):
```

```
    ext = os.path.splitext(file_path)[1].lower()
    if ext == ".csv":
        return pd.read_csv(file_path)
    elif ext == ".txt":
        return pd.read_csv(file_path, sep=None, engine="python")
    elif ext in [".xls", ".xlsx"]:
        return pd.read_excel(file_path)
    else:
        raise ValueError("Unsupported file format!")

# --- Generate LAS content ---
def generate_las(df, well_name):
    lines = []
    start_depth = df['Depth'].min()
    stop_depth = df['Depth'].max()
    step = df['Depth'].diff().dropna().mode()[0]  # most frequent step
    null_value = -999.25

    lines.append("~Version Information Section")
    lines.append("VERS.                  2.0           : CWLS LOG ASCII
STANDARD - VERSION 2.0")
    lines.append("WRAP.                  NO            : One line per depth
step\n")

    lines.append("~Well Information Section")
    lines.append("STRT.M                 {:.4f}         : START
DEPTH".format(start_depth))
    lines.append("STOP.M                 {:.4f}         : STOP
DEPTH".format(stop_depth))
    lines.append("STEP.M                 {:.4f}         : STEP".format(step))
    lines.append("NULL.                 {}           : NULL
VALUE".format(null_value))
    lines.append("COMP.                  UNKNOWN        : COMPANY")
    lines.append(f"WELL.                  {well_name}    : WELL NAME")
    lines.append("FLD.                   UNKNOWN        : FIELD")
    lines.append("LOC.                   UNKNOWN        : LOCATION")
    lines.append("PROV.                  UNKNOWN        : PROVINCE")
    lines.append("SRVC.                  UNKNOWN        : SERVICE COMPANY")
    lines.append("DATE.                  2025-06-14     : LOG DATE")
    lines.append("UWI.                   UNKNOWN        : UNIQUE WELL ID\n")

    lines.append("~Curve Information Section")
    lines.append("#MNEM.UNIT              API CODES    CURVE DESCRIPTION")
    for mnemonic, unit, desc in CURVE_INFO:
        lines.append(f"{mnemonic:<6}.{unit:<10}           : {desc}")
    lines.append("")

    lines.append("~ASCII Log Data")
    for _, row in df.iterrows():
        row_vals = [row.get(col, null_value) for col in ['Depth', 'GammaRay',
'Resistivity', 'Density', 'NeutronPorosity', 'SonicDT']]
        row_str = " ".join(f"{val:.4f}" if pd.notnull(val) else
f"{null_value:.2f}" for val in row_vals)
        lines.append(row_str)
```

```
    return "\n".join(lines)

# --- Save LAS file ---
def save_las_file(content, well_name):
    output_file = f"{well_name}.las"
    with open(output_file, "w") as f:
        f.write(content)
    print(f"LAS file saved as: {output_file}")


# --- Save LAS file to user-selected output folder ---
def save_las_file(content, well_name, output_folder):
    output_path = os.path.join(output_folder, f"{well_name}.las")
    with open(output_path, "w") as f:
        f.write(content)
    print(f"LAS file saved as: {output_path}")

# --- Main Process ---
def main():
    file_path = select_file()
    if not file_path:
        print("No file selected.")
        return

    output_folder = filedialog.askdirectory(title="Select Output Folder")
    if not output_folder:
        print("No output folder selected.")
        return

    df = read_data(file_path)

    # Handle column naming and filtering
    required_columns = ['WellName', 'Depth', 'GammaRay', 'Resistivity',
'Density', 'NeutronPorosity', 'SonicDT']
    for col in required_columns:
        if col not in df.columns:
            raise ValueError(f"Missing required column: {col}")

    for well_name, group_df in df.groupby("WellName"):
        group_df_sorted = group_df.sort_values("Depth")
        las_content = generate_las(group_df_sorted, well_name)
        save_las_file(las_content, well_name, output_folder)

if __name__ == "__main__":
    main()
```

3.2 LAS Header Extraction

In some QC workflows, only log header metadata are required. The following script extracts header sections (~V, ~W, ~C) and omits the ~A data block.

```
# extract_las_header.py
import os

for filename in os.listdir('.'):
    if filename.lower().endswith('.las'):
        with open(filename, 'r') as f:
            lines = f.readlines()

        # Open a new file to write the header
        with open(f"{filename}.header", 'w') as header_file:
            for line in lines:
                if '\176A' in line:  # Check for the marker \176A
                    break  # Stop when the data part starts
                header_file.write(line)
```

3.3 Standardizing LAS Null Values

Non-standard null representations (e.g., -9999 or -999.000) often cause issues during ingestion. This Python utility replaces them with -999.25 across multiple LAS files.

```
# ReplaceLASNull.py script to replace LAS Null values in multiple LAS files
e.g. -9999 into -999.25 in the Header and data_section ie. after ~A.
# take input CWLS LAS format from "curr_dir"  and save the edited in the
"output_dir"
#----------------------------------------------------------------

import glob
import os
import ntpath
import tkinter as tk
from tkinter import filedialog
import re  # Import the regular expression module

# Set up Tkinter root window (it won't appear because we use the dialog box)
root = tk.Tk()
root.withdraw()  # Hide the main Tkinter window

# Prompt user to select the input directory (curr_dir)
curr_dir = filedialog.askdirectory(title="Select the Input Directory with LAS
files")
if not curr_dir:
    print("No input directory selected. Exiting.")
    exit()

# Prompt user to select the output directory (output_dir)
output_dir = filedialog.askdirectory(title="Select the Output Directory to
Save Edited LAS files")
if not output_dir:
    print("No output directory selected. Exiting.")
    exit()

# Ensure the output directory exists
if not os.path.exists(output_dir):
    os.makedirs(output_dir)
```

```
# Regex pattern to match various forms of '-9999' and its decimal variants
pattern = r"-9999(\.0+)?(\.000+)?(\.0000+)?"

# Process each LAS file in the directory
for f in glob.glob(os.path.join(curr_dir, "*.las")):
    with open(f, 'r') as inputfile:
        # Create output file with the same name in the output directory
        output_file_path = os.path.join(output_dir, ntpath.basename(f))
        with open(output_file_path, 'w') as outputfile:
            is_data_section = False  # Flag to track the data section

            for line in inputfile:
                # If we encounter the data section (~A), we mark it
                if line.startswith("~A"):
                    is_data_section = True
                # If we encounter another section (~), we exit the data
section
                elif line.startswith("~") and is_data_section:
                    is_data_section = False

                # Replace matching values for all occurrences of '-9999' (in
header or data section)
                # Use Regex to replace all versions of '-9999' with '-999.25'
                line = re.sub(pattern, "-999.25", line)

                # Write the (possibly modified) line to the output file
                outputfile.write(line)

print("Processing complete. Edited files saved in:", output_dir)
```

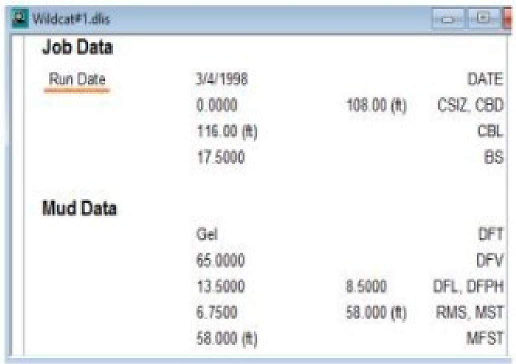
3.4 Standardizing Date Formats

Standardizing date formats is essential to maintain consistency across domains and disciplines. In well logging; whether Wireline or LWD/MWD and Cased-Hole— date and time are critical metadata for log data quality and traceability (Theys, 1999). A unified date format ensures that all specialists can correctly interpret and utilize the data without ambiguity.

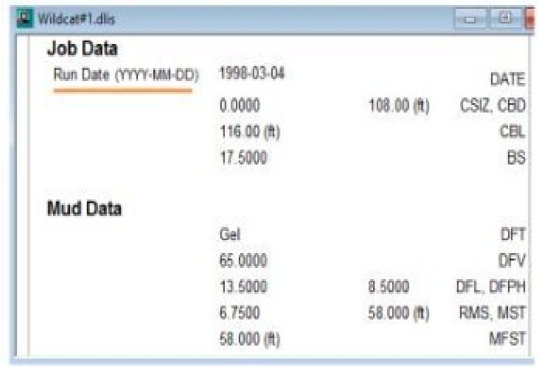
Adopting a standardized date format provides several benefits:

- **Prevents Misinterpretation:** Numerical date formats can be ambiguous (e.g., sample #1), whereas an ISO-compliant format (ISO 8601) ensures clarity (e.g., sample #2)

Sample# 1



Sample# 2 using ISO 8601 Date and Time format



- **Enhances Search and Sorting:** Standardized dates simplify querying and filtering data
- **Ensures System Consistency:** Uniform formatting across platforms reduces discrepancies when integrating multiple data sources.
- **Improves Data Exchange:** A consistent standard avoids errors in interpreting time and date when sharing data across systems and applications.

Best Practices for Standardizing Date Formats in Techlog

Normalize Upon Import.

Convert all incoming log timestamps to the **ISO 8601** standard format (e.g., YYYY-MM-DDThh:mm:ssZ) to ensure consistency across datasets. Apply this conversion to:

- **LAS headers** — DATE field
- **DLIS acquisition timestamps** — run or recording date
- **Drilling metadata** — bit depth vs. time records

Set a Clear Time Zone Policy

Use **UTC** as the master time reference for all log data. If local time is required for operational or reporting purposes, record the **local time offset** separately in metadata or header fields.

Validate During QC Checks

Leverage **Techlog QC modules** to automatically identify and correct issues such as:

- Missing or invalid timestamps
- Clock drift between tools or runs
- Overlapping log intervals
- Time/depth mismatch warnings

Document Within Metadata
clearly record the adopted date and time standard within **job headers, log metadata, and data delivery specifications**. This ensures transparency and consistency across workflows, teams, and data platforms.

4. Manual Editing Techniques (DLIS Header Modification)

DLIS files, defined under API RP 66, are binary and not human-readable. When specialized software is unavailable, for example, during quick QC checks in the field, or when license-based applications are temporarily inaccessible. In these cases, a simple but powerful alternative is to use a hexadecimal editor like HexEdit 4.0. This lightweight utility allows users to directly view and adjust DLIS header parameters such as Well Name safely without needing a full petrophysical platform.

Step-by-Step Procedure

1. Download HexEdit 4.0 (free) software from the CNET Download website https://download.cnet.com/HexEdit/3000-2352_4-10208432.html

2. After extracting the HexEdit4_0 .zip file to your working folder, run the HexEd4_0.msi file and follow the instructions

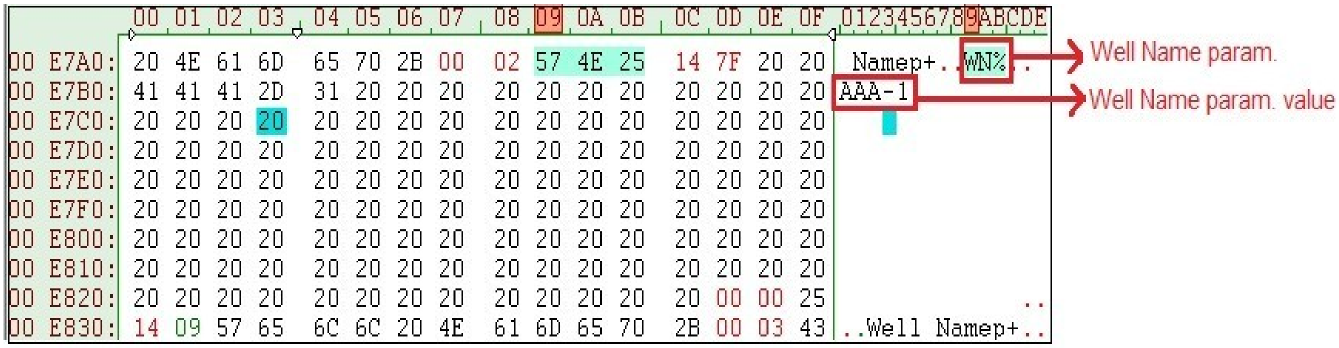
3. Launch the HexEdit app, then open a DLIS file by clicking on the File menu and selecting Open, or by pressing **Ctrl-O**

4. Navigate to the folder containing the DLIS files whose well header parameters you want to update. **Ensure you have backed up your DLIS files** before performing this task

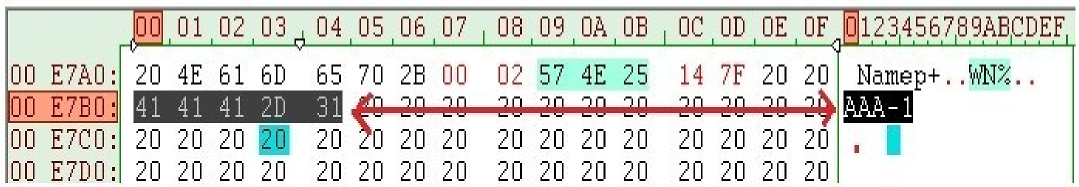
5. Once a DLIS file is displayed in HexEdit, the left column—Hex column—shows the raw numbers, while the right column displays a textual representation of the DLIS file

6. To change the Well Name, use the Edit > Find menu or press Ctrl-F. Then, select the Text tab to search, enter 'WN%' in the Text find field, and click the Find Next button. (WN is the parameter mnemonic code for Well Name)

Text find/search result will looks like below:



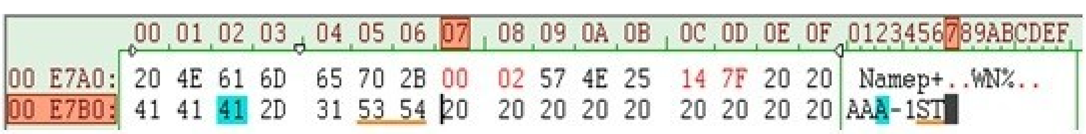
7. Right after WN% character is existing Well name value, in given sample is AAA-1. Note that when you highlight AAA-1 characters, in the same time in left column its corresponding hexadecimal values (41 41 41 2D 31) is highlighted



8. For instance, if you want to add 'ST' character (Hexadecimal: 5354)-- to indicate a side-track borehole, after AAA-1, go to left column and highlight hexadecimal number after the last hexadecimal number of Well name, which is 20

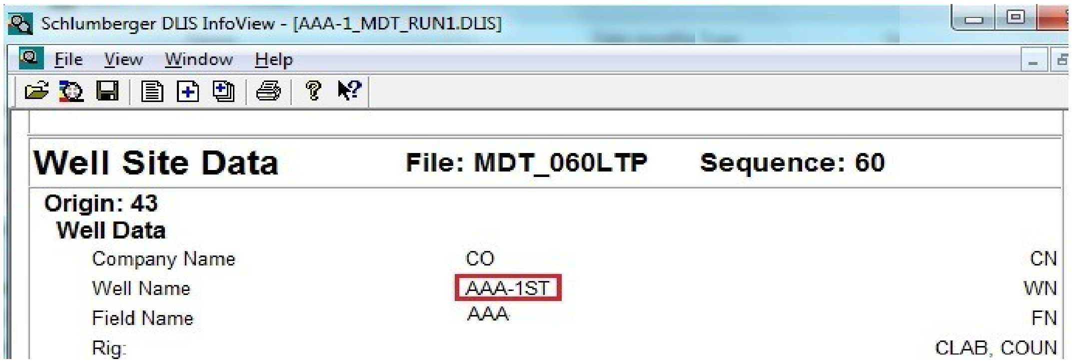
9. Put cursor in hexadecimal number 20, right click and clicking on 'Allow Changes', this needed to change Well name characters using allocated/existing internal storage. ⚠ **Do NOT** choose **Insert** or **Alt-I** command when editing hexadecimal values-- this will corrupt your DLIS file. Always modify within the existing byte allocation.

Type 53 54, you will see immediately in right column new characters 'ST' is added



10. Clicking on Save toolbar or press **Ctrl-S** to apply the changes

11. Validate the changes by opening the updated DLIS file in any DLIS viewer app. In this example, we use DLIS InfoView, a freeware data utility from SLB. You should now see the Well Name changed to AAA-1ST, while the other DLIS header parameters and channels/curves data remain the same.



Tips and Cautions

⚠ Do NOT use the 'Insert' or 'Alt+I' command when editing hexadecimal values — this will corrupt your DLIS file. Always modify within the existing byte allocation. Always validate the modified file in a DLIS viewer before final delivery or further processing.

Editing DLIS headers using HexEdit is a simple yet effective technique, especially in environments where specialized tools are unavailable. It helps maintain data quality and consistency during time-critical operations. With careful attention, this approach ensures well log data remains intact, reliable, and ready for further analysis.

5. Data Cleansing Workflows for Handling Non-Printable Characters in Spreadsheet-based datasets

We cannot see the **"Invisible Man"** directly–otherwise, he would not be invisible–but his presence can often be detected in our spreadsheets. One error he inserted you can clearly see, but the others are far harder to spot with the naked eye, such as:

1. Added extra white spaces at the ends of entries
2. Tabs that are inserted at the ends of lines
3. Line breaks (or Alt+Enter) and 'carriage returns', which you insert by pressing enter (or Ctrl-Enter).

These **"non-printable"** characters don't always appear on screen, yet they can quietly disrupt your data analysis. Spreadsheets treat them as real data, meaning four identicallooking entries may actually be read as four different values. So when you try to count how many times "Your Data" appears, you might get only one result– even though you can clearly see multiple.

That's the Invisible Man at work. To address this issue, a practical Python helper script – TheInvisibleMan.py–has been provided to automatically detect and remove these non-printable characters, ensuring cleaner, more reliable data for downstream analysis.

```
# TheInvisibleMan.py
import os
import re
import tkinter as tk
from tkinter import filedialog, messagebox
import pandas as pd


# Regex to remove non-printable characters
NON_PRINTABLE_REGEX = re.compile(r"[^\x20-\x7E]\s*")



def clean_string(value):
    """Clean a cell by removing:
    1) Non-printable characters
    2) Extra whitespace at ends
    3) Tabs, newlines, carriage returns
    """
    if pd.isna(value):
        return value

    if not isinstance(value, str):
        return value

    # Replace tabs, newlines, carriage returns with space
    value = value.replace("\t", " ").replace("\n", " ").replace("\r", " ")

    # Remove non-printable characters using regex
    value = NON_PRINTABLE_REGEX.sub("", value)
```

```
    # Strip extra whitespace
    value = value.strip()

    return value


def clean_excel_file(filepath):
    df_dict = pd.read_excel(filepath, sheet_name=None)
    cleaned_dict = {}
    for sheet, df in df_dict.items():
        cleaned_df = df.applymap(clean_string)
        cleaned_dict[sheet] = cleaned_df

    base, ext = os.path.splitext(filepath)
    new_path = f"{base}_Cleaned{ext}"
    with pd.ExcelWriter(new_path, engine="openpyxl") as writer:
        for sheet, cleaned_df in cleaned_dict.items():
            cleaned_df.to_excel(writer, sheet_name=sheet, index=False)

    return new_path


def browse_and_clean():
    files = filedialog.askopenfilenames(
        title="Select Excel Files",
        filetypes=[("Excel files", "*.xlsx *.xls")]
    )

    if not files:
        return

    for f in files:
        new_file = clean_excel_file(f)
```

```
        print(f"Saved cleaned file: {new_file}")


    messagebox.showinfo("Done", "All selected Excel files have been
cleaned.")



if __name__ == "__main__":
    root = tk.Tk()
    root.title("Excel TheInvisibleMan cleaner")


    button = tk.Button(root, text="Browse & Clean Excel Files",
command=browse_and_clean)
    button.pack(padx=20, pady=20)


    root.mainloop()
```

6. Conclusion

Consistent digital log data preparation underpins reliable petrophysical analysis and interpretation. Through automated validation, null values standardization, structured file conversion and for handling "non-printable" characters, practitioners can ensure LAS and DLIS datasets are fit-for-purpose, reproducible, and petrophysical package and data platform-compliant. The workflows presented here complement formal data management standards and can be easily customized or integrated into corporate QC pipelines.

Data Engineering Basics with Linux and SQL Tools, and GenAI-Assisted Workflows for Subsurface Reports

Why Data Engineering Matters in Well Log Workflows– *From files to databases to ML*

In modern subsurface workflows, well log data rarely remain as isolated LAS or DLIS files. After acquisition and QC, data are commonly transferred to shared file systems, loaded into databases, or ingested into data platforms before being analyzed or used in ML workflows. Data engineering provides the practical foundation that enables this transition– from file-based log data to queryable, scalable, and ML-ready datasets.

For petrophysicists and subsurface data practitioners, a basic understanding of data engineering concepts and tools improves the ability to perform systematic data screening before interpretation, support scalable QC and preprocessing, and enable reproducible ML-augmented petrophysical workflows.

1. Linux Basics for Log Data Processing

Linux is the **glue** that holds subsurface data pipelines together.

Essential Commands (with subsurface use cases)

Command	Why it matters
ls, cd, pwd	Navigate well / field / asset directories
cp, mv, rm	Manage LAS, CSV, export files
head, tail, less	Quick look at large log or production files
wc -l	Count depth samples or records
grep	Search mnemonics, well names, QC flags
cut, awk	Extract columns (e.g., depth, GR, RHOB)
sort, uniq	Find duplicates (well names, UWI, dates)

Command	Why it matters
sed	Fix headers, units, delimiters
find	Locate LAS files by well or date

Navigating directories:

```
pwd
ls
cd well_logs/Field_A/WELL_01
```

Batch operations:

```
find . -name "*.las"
mkdir qc_results validated_logs
cp *.dlis backup_dlis/
```

Quick checks:

```
head -40 WELL_01.las
tail WELL_01.las
```

Identify wells containing Sonic logs:

```
grep -i "DT" WELL_01.las
```

Running Python scripts:

```
python LASValidatorv2-free.py
```

Linux pipeline:

```
cat prod_2024.csv | grep -v "NULL" | awk -F',' '{print $1,$3,$5}'
```

2. SQL Fundamentals

Structured subsurface metadata–such as well headers, log curve inventories, and depth intervals–are commonly stored in relational databases. Structured Query Language (SQL) provides a simple and transparent way to assess data completeness and readiness before interpretation or ML workflow.

Core SQL 'SELECT' Concepts:

SELECT – retrieve required information
WHERE – filter wells, curves, or intervals
GROUP BY – summarize and audit datasets
ORDER BY – sorting results

Example: Identify wells missing Sonic (DT) logs

```
SELECT DISTINCT w1.wellbore_name
FROM well_log_inventory w1
WHERE NOT EXISTS (
   SELECT 1
   FROM well_log_inventory w2
   WHERE w2.wellbore_name = w1.wellbore_name
     AND w2.curve_mnemonic = 'DT'
);
```

Example: List available curves per well

```
SELECT wellbore_name, COUNT(DISTINCT curve_mnemonic) AS curve_count
FROM well_log_inventory
GROUP BY wellbore_name;
```

Example: Check depth coverage consistency

```
SELECT wellbore_name,
       MIN(start_depth) AS start_depth,
       MAX(stop_depth) AS stop_depth
FROM well_log_intervals
GROUP BY wellbore_name;
```

3. GenAI-Assisted workflow for Subsurface Reports

The objective of GenAI-assisted data engineering workflow is to demonstrate how Generative AI tools such as OpenAI ChatGPT https://chatgpt.com or Google Gemini https://gemini.google.com/app can be used to augment traditional data handling tasks, specifically when working with unstructured subsurface reports such as Final Well Reports (FWR) or End of Well Reports (EOWR).

The workflow focuses on three core steps:
1) Uploading a subsurface report,
2) Summarizing key well data and facts, and
3) Exporting structured data into Excel for further analysis or database loading.

This approach is intended to complement, not replace, domain expertise, data governance practices, and existing well data management systems.

1. Uploading a Subsurface Report (Unstructured Data Input)

Subsurface reports such as Final Well Reports are typically delivered in PDF or Word format and contain large volumes of unstructured text, tables, and technical terminology. These documents often include critical information such as well metadata, drilling timelines, formation tops, casing programs, and operational events.

Using GenAI tools:

- Upload the report directly into the GenAI interface (where supported).
- Ensure the document is complete and legible (scanned PDFs should be text-searchable).
- Clearly state the context (e.g., “This is a Final Well Report for a development well”).

2. Summarizing Key Well Data and Facts

Once the report is uploaded, GenAI can be prompted to extract and summarize key well information. Typical data elements include:
- Well name and wellbore identifier
- Spud date and total depth date
- Total depth (Measured Depth and/or True Vertical Depth)
- Formation tops
- Hole sections and casing details
- Key drilling events, challenges, or non-productive time (NPT)

Example prompt:
"*Summarize the key well data, drilling dates, depths, formation tops, and casing information from this Final Well Report. Present the results in a structured table*"

The output should be reviewed carefully by the user to:

- Validate numerical values and units
- Ensure naming consistency with corporate or database standards
- Confirm alignment with the original report

This **human-in-the-loop** validation step is essential for maintaining data quality and trust.

3. Structuring and Exporting Data to Excel

After validation, the summarized data can be organized into a structured, tabular format suitable for Excel. Common Excel worksheets may include:
- Well Header Information
- Formation Tops
- Hole and Casing Sections
- Key Operational Events

The final step is to export the structured data into Excel (.xlsx) format. This Excel file can then be:

- Used for QA/QC and review
- Shared with geoscience and engineering teams
- Loaded into databases
- Integrated into analytics or visualization workflows

Professional Considerations and Best Practices.

While GenAI significantly improves efficiency, the following best practices should always be observed:

- Treat GenAI outputs as draft results requiring validation
- Maintain clear data ownership and accountability. Ensure sensitive or proprietary data complies with company data policies

- Document assumptions, prompts, and validation steps

Conclusion

GenAI-assisted data engineering provides a practical and accessible way to transform unstructured subsurface reports into structured, analytics-ready datasets. When used responsibly, this workflow can reduce manual effort, improve consistency, and accelerate data availability, while preserving the critical role of domain expertise in subsurface data management.

Data-Driven Petrophysical Applications: Practical Use Cases in Log QC, Synthetic Log Generation, and Multi-Well Rock Typing

1. Introduction

The upstream oil and gas industry is experiencing a significant digital transformation. Data-driven workflows are redefining how subsurface professionals acquire, process, and interpret well log data. Well logs, derived from wireline, LWD, and MWD tools and supported by core measurements, remain essential for petrophysical interpretation, reservoir characterization, optimal well placement, and informed production decision-making.

Despite technological advances, well log data often suffer from quality and completeness challenges. Issues such as tool calibration drift, borehole irregularities, missing log curves, or inconsistent data formats persist across projects.

These problems increase uncertainty in interpretation and slow decision-making.

Artificial Intelligence (AI), through the use of Machine Learning (ML) techniques, represents a paradigm shift by enabling systems to learn from data, make predictions, and improve performance autonomously, transforming traditional approaches to problem-solving. Instead of relying solely on manual QC or deterministic equations, petrophysicists can apply ML models to automate repetitive processes, discover hidden patterns, and augment interpretation accuracy. Data-driven techniques enable reproducibility, scalability, and objective validation of log-derived interpretations.

This guideline currently covers four practical and complementary ML-augmented petrophysical applications: **Outlier Detection for Log Quality Control**, **Synthetic Sonic Log Generation**, **Multi-Well Rock Typing using Clustering** and **Porosity Prediction from Conventional Logs**.

1. Outlier Detection for Log QC – detecting anomalous log readings due to measurement artifacts or borehole effects using algorithms such as Isolation Forest and DBSCAN.
2. Synthetic Sonic Log Generation – predicting missing Sonic (DT) log values using regression models like Random Forest and XGBoost.
3. Multi-Well Rock Typing with Clustering – grouping multi-well log data into electrofacies using unsupervised clustering methods such as K-Means or Gaussian Mixture.
4. Porosity Prediction from Conventional Logs – augmented approach for predicting porosity using a conventional suite of well logs: GR, RHOB, NPHI, RT, and Sonic DT.

Each use case demonstrates a data-centric workflow where ML complements domain expertise to ensure data integrity, improve interpretive consistency, and support integrated reservoir modeling.

2. Use Case 1: Outlier Detection for Log QC

2.1 Background

Well log anomalies or “spikes” often arise from sensor malfunction, tool sticking, borehole washouts, or transmission errors. If undetected, these artifacts distort computed properties such as porosity or water saturation. Traditional QC relies heavily on manual visual checks—time-consuming and subjective.

Unsupervised anomaly detection using ML can automate this process. The Isolation Forest (IF) algorithm isolates anomalous data points by randomly selecting features and split values to create decision trees. Outliers are identified by their short average path length in the tree structure, making the method efficient for large datasets.

2.2 Workflow Overview

1. Data Loading– Read LAS files using `lasio`, extract curves such as GR, RHOB, and NPHI.
2. Preprocessing– Handle null values, align depths, and standardize input features.

3. Anomaly Detection– Train Isolation Forest or DBSCAN to detect spikes.
4. Visualization & Review– Plot flagged data for inspection and validation.

5. Correction– Replace outliers via interpolation or smoothing filters.

LogsSpikeDetection_IsoForest.py

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.ensemble import IsolationForest
import lasio
from tkinter import Tk, filedialog

# Function to load LAS files interactively
def load_las_files():
    Tk().withdraw()  # Hide the root window
    file_paths = filedialog.askopenfilenames(
        title="Select LAS File(s)",
        filetypes=[("LAS Files", "*.las")]
    )
    return file_paths

# Process each LAS file
def process_las_file(file_path, curve_name):
    las = lasio.read(file_path)
    if curve_name not in las.curves:
        raise ValueError(f"Curve '{curve_name}' not found in {file_path}")

    # Extract depth and specified curve
    depth = las["DEPT"]  # Assuming 'DEPT' is the depth curve name
    curve_data = las[curve_name]

    # Create a DataFrame
    data = pd.DataFrame({'Depth': depth, curve_name: curve_data})

    # Detect spikes using Isolation Forest
    iso_forest = IsolationForest(contamination=0.01, random_state=42)
    data['Anomaly_Score'] = iso_forest.fit_predict(data[[curve_name]])
    data['Anomaly'] = data['Anomaly_Score'] == -1

    # Plot the curve with anomalies highlighted
    plt.figure(figsize=(10, 6))
    plt.plot(data['Depth'], data[curve_name], label=curve_name, color='blue')
    plt.scatter(data['Depth'][data['Anomaly']], data[curve_name]
[data['Anomaly']],
                color='red', label='Detected Spikes', zorder=5)
    plt.xlabel('Depth (m)')
    plt.ylabel(f'{curve_name} (API)')
    plt.title(f'{curve_name} Log with Detected Spikes in {file_path}')
```

```
    plt.legend()
    plt.show()

# Main script
if __name__ == "__main__":
    print("Select LAS file(s) for processing...")
    las_files = load_las_files()

    if not las_files:
        print("No files selected. Exiting.")
    else:
        curve_name = input("Enter the curve name to process (e.g., GR for
Gamma Ray): ").strip()
        for file_path in las_files:
            try:
                print(f"Processing file: {file_path}")
                process_las_file(file_path, curve_name)
            except Exception as e:
                print(f"Error processing {file_path}: {e}")
```

2.3 Discussion

The Isolation Forest efficiently highlights outliers corresponding to spikes or sensor errors. Visual inspection confirms that flagged points typically coincide with acquisition noise or tool sticking. DBSCAN may also be used where anomalies form small, dense clusters.

This ML-based QC approach standardizes the process across wells, improves reproducibility, and significantly reduces manual QC time. It ensures a clean input dataset before performing reservoir property estimation or synthetic log prediction.

3. Use Case 2: Synthetic Sonic Log Generation

3.1 Background

Sonic travel-time (DT) logs are essential for porosity estimation, geomechanics, and seismic-well tie. However, missing DT data is common due to tool failure, environmental limitations, or economic constraints. Traditional imputation using empirical correlations (e.g., Gardner or Castagna) assumes fixed relationships that may not hold across lithologies.

Machine learning provides a flexible, data-driven solution. By training regression models on available logs— such as Gamma Ray (GR), Density (RHOB), Neutron Porosity

(NPHI), and Resistivity— missing DT can be accurately predicted. Models like Random Forest or XGBoost capture nonlinear dependencies between features.

3.2 Workflow Steps

1. Data Preparation– Two wells are used: WELL_1 with full logs (training), WELL_2 with missing DT (prediction).
2. Feature Engineering– Normalize predictors and ensure consistent log naming.
3. Model Training– Train Random Forest using GR, RHOB, NPHI, and Resistivity as inputs.
4. Cross-Validation – Use 5-fold CV to measure model reliability via Mean Squared Error (MSE).
5. Prediction & Export– Apply trained model to WELL_2 to generate synthetic SonicDT and save as Techlog-ready CSV.

generate_SonicDT_log_x-val.py

```
import pandas as pd
import numpy as np
from sklearn.ensemble import RandomForestRegressor
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import cross_val_score

# Load WELL_1 and WELL_2 data
data_well_1 = pd.read_csv("well_log_data_WELL_1.csv")  # Replace with your
actual file paths
data_well_2 = pd.read_csv("well_log_data_WELL_2.csv")

# Add WellName to distinguish between the two wells
data_well_1['WellName'] = 'WELL_1'
data_well_2['WellName'] = 'WELL_2'

# Combine the data into a single DataFrame
data = pd.concat([data_well_1, data_well_2], axis=0)

# Extract rows where Sonic DT is missing for WELL_2
missing_sonic_dt = data[(data['WellName'] == 'WELL_2') &
data['SonicDT'].isna()]

# Extract rows where Sonic DT is available for WELL_1 (training data)
training_data = data[data['WellName'] == 'WELL_1']

# Define features (excluding SonicDT)
features = ['GammaRay', 'Resistivity', 'Density', 'NeutronPorosity']
#features = ['Depth','GammaRay', 'Resistivity', 'Density', 'NeutronPorosity']
```

```
# Prepare the training data (features and target)
X = training_data[features]
y = training_data['SonicDT']

# Normalize the features (optional)
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Initialize the RandomForestRegressor model
model = RandomForestRegressor(n_estimators=100, random_state=42)

# Perform cross-validation (e.g., 5-fold cross-validation)
cv_scores = cross_val_score(model, X_scaled, y, cv=5,
scoring='neg_mean_squared_error')

# The negative mean squared error needs to be converted to positive
cv_scores = -cv_scores

# Output the cross-validation results
print(f"Cross-Validation Mean Squared Errors: {cv_scores}")
print(f"Average Cross-Validation MSE: {cv_scores.mean()}")

# Train the model on the entire training data (since cross-validation is just
for evaluation)
model.fit(X_scaled, y)

# Prepare the missing data from WELL_2 for prediction
X_missing = missing_sonic_dt[features]
X_missing_scaled = scaler.transform(X_missing)

# Predict the missing Sonic DT values for WELL_2
predicted_sonic_dt = model.predict(X_missing_scaled)

# Fill in the missing values in the original data for WELL_2
data.loc[data['SonicDT'].isna() & (data['WellName'] == 'WELL_2'), 'SonicDT']
= predicted_sonic_dt

# Extract only the rows for WELL_2 with the filled Sonic DT values
well_2_filled = data[data['WellName'] == 'WELL_2']

# Save the updated WELL_2 data to a new CSV file
well_2_filled.to_csv("well_log_data_WELL_2_SonicDT_added.csv", index=False)

# Optional: You can also print out a message indicating the CSV file was
saved
print("CSV file with added Sonic DT values for WELL_2 has been saved as
'well_log_data_WELL_2_SonicDT_added.csv'")
```

3.3 Validation and Results

Validation ensures the predicted DT curve aligns with geological expectations.

Crossplots (e.g., RHOB vs. NPHI) and depth-track comparisons between measured and synthetic DT help assess consistency. A good correlation ($R^2 > 0.9$) indicates reliability.

3.4 Discussion

Compared to empirical models, ML regression captures multi-dimensional relationships between logs, making it more adaptable across lithofacies. The approach enhances data completeness, enabling continuous velocity modeling, porosity estimation, and seismic interpretation. Synthetic log generation can be scaled to field-wide datasets once trained.

4. Use Case 3: Multi-Well Rock Typing with Clustering

4.1 Background

Multi-Well Rock typing links petrophysical data with geological facies and flow properties. Manual classification from core or thin sections is often limited in depth and coverage. By contrast, data-driven clustering uses continuous log data to classify electrofacies across multiple wells, improving consistency and scalability.

4.2 Workflow Steps

1. Data Preparation– Merge multi-well log datasets containing GR, RHOB, NPHI, and DT.
2. Standardization– Apply z-score normalization to prevent scale bias.
3. Clustering– Apply K-Means or Gaussian Mixture Models (GMM) to assign electrofacies clusters.
4. Facies Mapping– Relate cluster means to lithology using GR or core data.
5. Visualization– Generate crossplots and facies depth tracks for interpretation.

MultiWell_RockTyping_using_logs.py

```
#-- Multi-Well Rock Typing (Electrofacies Classification using #Well Logs)
# Objective: Automatically cluster multiple wells' log responses (GR, RHOB,
NPHI, DT) into consistent electrofacies.
# Use Case:

import pandas as pd
import numpy as np
import os
from sklearn.preprocessing import StandardScaler
```

```
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt
from tkinter import Tk, filedialog

# --- Step 1: Browse & Select Multiple Well Files ---
root = Tk()
root.withdraw()  # Hide main Tkinter window
file_paths = filedialog.askopenfilenames(
    title="Select Well Log CSV Files",
    filetypes=[("CSV files", "*.csv")]
)
root.update()

if not file_paths:
    raise FileNotFoundError("⚠ No CSV files selected. Please select one or
more well log files.")

dataframes = []
for file in file_paths:
    well_name = os.path.splitext(os.path.basename(file))
[0].replace("well_logs_", "")
    df = pd.read_csv(file)
    df["Well"] = well_name
    dataframes.append(df)

# Combine all selected wells
df_all = pd.concat(dataframes, ignore_index=True)
print(f"✅ Loaded {len(file_paths)} wells, total samples: {len(df_all)}")

# --- Step 2: Feature Selection & Scaling ---
features = ["GR", "RHOB", "NPHI", "DT"]
df_all = df_all.dropna(subset=features)  # Remove rows with missing key logs

X_scaled = StandardScaler().fit_transform(df_all[features])

# --- Step 3: K-Means Clustering (Global Model) ---
n_clusters = 4
kmeans = KMeans(n_clusters=n_clusters, random_state=42)
df_all["Electrofacies"] = kmeans.fit_predict(X_scaled)

# --- Step 4: Facies Labeling (Based on Mean GR) ---
cluster_summary = df_all.groupby("Electrofacies")[["GR", "RHOB",
"NPHI"]].mean()
print("\nCluster Summary (All Wells):\n", cluster_summary)

facies_map = {}
gr_means = cluster_summary["GR"].sort_values()
for cluster in gr_means.index:
    if gr_means[cluster] < 80:
        facies_map[cluster] = "Sandstone"
    elif gr_means[cluster] < 100:
        facies_map[cluster] = "Siltstone"
    else:
        facies_map[cluster] = "Shale"
```

```
df_all["Facies_Label"] = df_all["Electrofacies"].map(facies_map)

# --- Step 5: Visualization Example (One Well) ---
plt.figure(figsize=(6, 5))
subset = df_all[df_all["Well"] == df_all["Well"].unique()[0]]
for label in subset["Facies_Label"].unique():
    part = subset[subset["Facies_Label"] == label]
    plt.scatter(part["GR"], part["RHOB"], label=label, s=40)
plt.xlabel("Gamma Ray (API)")
plt.ylabel("Bulk Density (g/cc)")
plt.title(f"Electrofacies Crossplot (Example Well:
{subset['Well'].iloc[0]})")
plt.legend()
plt.show()

# --- Step 6: Depth Track Visualization per Well ---
facies_colors = {"Sandstone": "gold", "Siltstone": "green", "Shale": "gray"}
for well in df_all["Well"].unique():
    wdf = df_all[df_all["Well"] == well]
    plt.figure(figsize=(3, 8))
    plt.scatter(wdf["Facies_Label"], wdf["Depth"],
c=wdf["Facies_Label"].map(facies_colors), s=25)
    plt.gca().invert_yaxis()
    plt.xlabel("Facies")
    plt.ylabel("Depth (m)")
    plt.title(f"Facies vs Depth Track: {well}")
    plt.show()

# --- Step 7: Save Combined Techlog-Ready Output ---
output_cols = ["Well", "Depth", "Electrofacies", "Facies_Label"]
output_file = "field_electrofacies_combined.csv"
df_all[output_cols].to_csv(output_file, index=False)

print(f"\n✅ Combined Techlog-ready electrofacies file saved as:
{output_file}")
print(f"Includes {len(df_all)} total samples from {len(file_paths)} wells.")
```

4.4 Interpretation and Discussion

Cluster analysis enables the identification of distinct lithologic groupings—for example, low gamma-ray (GR) values combined with high bulk density (RHOB) typically indicate sandstone units, whereas high GR and lower RHOB are commonly associated with shale intervals. When core-derived lithofacies are available, validating the cluster results against these ground-truth observations significantly improves interpretation confidence.

The resulting electrofacies can be visualized as color-coded log tracks alongside conventional curves or exported for incorporation into reservoir characterization and geomodeling workflows.

Clustering-based rock typing ensures consistency across wells, reduces interpreter bias, and supports scalable facies modeling. GMM can provide probabilistic facies assignment where transitions are gradual.

5. Use Case 4: Predicting Porosity using a conventional suite of well logs (GR, RHOB, NPHI, RT, DT)

5.1 Background

This workflow introduces a machine learning–augmented approach for predicting porosity using a conventional suite of well logs: Gamma Ray (GR), Bulk Density (RHOB), Neutron Porosity (NPHI), Resistivity (RT), and Compressional Sonic (DT).

Unlike traditional deterministic methods– which often require manual, well-by-well calibration– this approach is explicitly designed for multi-well, field-scale applications. By learning from integrated datasets across many wells, the model captures consistent relationships between log responses and porosity that are difficult to maintain through manual interpretation alone.

By leveraging this approach, the workflow enables:

- Field-Wide Consistency
  Establishes a unified, data-driven relationship between log responses and porosity across the entire asset, reducing interpreter bias and variability.
- Scalable Execution
  Supports rapid deployment across large well inventories, enabling hundreds of wells to be processed efficiently and consistently.
- Enhanced Predictive Capability
  Integrates the combined physical responses of multiple log types, allowing the model to better handle complex lithologies, fluid effects, and non-linear relationships.

Overall, this workflow transforms porosity estimation from a localized, manual task into a scalable and reproducible data-driven process, ensuring that reservoir models are built on a consistent, transparent, and technically robust foundation.

As with all ML-based methods presented in this book, this approach is intended to complement– not replace– conventional petrophysical interpretation.

5.2 Workflow Steps

porosity_prediction.py

```
"""
porosity_prediction.py

Objective:  ML workflow to predict Porosity from conventional logs
(GR, RHOB, NPHI, RT, DT).

Designed for:
- Large mature fields with many wells
- Consistent and scalable porosity prediction

Features:
- Tkinter file browser (CSV / LAS)
- Robust preprocessing
- Random Forest regression
- Cross-validation
- Model versioning by Field + Date

Author: Edy Irnandi Sudjana
License: MIT
"""

import os
import joblib
import numpy as np
import pandas as pd

from datetime import datetime
from tkinter import Tk, filedialog

from sklearn.model_selection import train_test_split, cross_val_score, KFold
from sklearn.ensemble import RandomForestRegressor
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.impute import SimpleImputer
from sklearn.metrics import mean_squared_error, r2_score

# Optional LAS support
try:
    import lasio
    HAS_LASIO = True
except Exception:
    HAS_LASIO = False
```

```
# -------------------------
# 1. File Selection
# -------------------------
def browse_file():
    Tk().withdraw()
    return filedialog.askopenfilename(
        title="Select CSV or LAS Well Log File",
        filetypes=[("CSV files", "*.csv"), ("LAS files", "*.las"), ("All
files", "*.*")]
    )


# -------------------------
# 2. Data Loading
# -------------------------
def load_data(filepath):
    ext = os.path.splitext(filepath)[1].lower()

    if ext == ".csv":
        return pd.read_csv(filepath)

    if ext == ".las":
        if not HAS_LASIO:
            raise ImportError("Install lasio to read LAS files.")
        las = lasio.read(filepath)
        df = las.df().reset_index()
        df.rename(columns={'DEPT': 'Depth'}, inplace=True)
        return df

    raise ValueError("Unsupported file format.")


# -------------------------
# 3. Feature Preparation
# -------------------------
def prepare_features(df, feature_cols, target_col):
    df = df.copy()

    # Drop rows without porosity (training only)
    df = df.dropna(subset=[target_col])

    X = df[feature_cols]
    y = df[target_col].values

    # Robust imputation for mature fields
    imputer = SimpleImputer(strategy="median")
    X = imputer.fit_transform(X)

    return X, y


# -------------------------
# 4. Model Builder
```

```
# -------------------------
def build_model():
    return Pipeline([
        ('scaler', StandardScaler()),
        ('model', RandomForestRegressor(
            n_estimators=300,
            random_state=42,
            n_jobs=-1
        ))
    ])


# -------------------------
# 5. Evaluation
# -------------------------
def evaluate(model, X_test, y_test):
    preds = model.predict(X_test)
    rmse = np.sqrt(mean_squared_error(y_test, preds))
    r2 = r2_score(y_test, preds)

    print(f"Porosity → RMSE = {rmse:.4f}")
    print(f"Porosity → R²   = {r2:.4f}")


# -------------------------
# 6. MAIN WORKFLOW
# -------------------------
if __name__ == "__main__":

    print("Select your input CSV/LAS well log file...")
    file_path = browse_file()

    if not file_path:
        print("No file selected. Exiting.")
        exit()

    print(f"\nLoading file: {file_path}")
    df = load_data(file_path)

    FEATURES = ['GR', 'RHOB', 'NPHI', 'RT', 'DT']
    TARGET = 'Porosity'

    FEATURES = [c for c in FEATURES if c in df.columns]

    if not FEATURES:
        raise ValueError("No valid predictor logs found.")

    if TARGET not in df.columns:
        raise ValueError("Porosity column not found.")

    X, y = prepare_features(df, FEATURES, TARGET)

    X_train, X_test, y_train, y_test = train_test_split(
        X, y, test_size=0.2, random_state=42
```

```
    )

    model = build_model()

    print("\nRunning 5-fold cross-validation...")
    kf = KFold(n_splits=5, shuffle=True, random_state=42)
    cv_mse = -cross_val_score(
        model, X_train, y_train,
        cv=kf,
        scoring='neg_mean_squared_error'
    )
    print("CV RMSE (Porosity):", np.sqrt(cv_mse).round(4))

    print("\nTraining porosity prediction model...")
    model.fit(X_train, y_train)

    print("\nModel Performance on Test Data:")
    evaluate(model, X_test, y_test)

    #
-----------------------------------------------------------------------------
---------------------------------------------------
    # Save model with versioning
    # note that Save model is responsible for persisting (saving) the trained
ML model to disk, so it can be reused later without retraining
    #
-----------------------------------------------------------------------------
---------------------------------------------------
    FIELD_NAME = "MatureField_A"   # change as needed
    RUN_DATE = datetime.now().strftime("%Y%m%d")

    model_dir = os.path.join(
        "saved_model",
        FIELD_NAME,
        RUN_DATE
    )

    os.makedirs(model_dir, exist_ok=True)

    model_filename = f"porosity_rf_model_{FIELD_NAME}_{RUN_DATE}.joblib"
    model_path = os.path.join(model_dir, model_filename)

    joblib.dump(model, model_path)

    print(f"\nModel saved to: {model_path}")
```

6. Discussion and Integration

The four workflows collectively demonstrate how ML strengthens the digital subsurface value chain. Outlier detection ensures data quality, synthetic log generation improves data completeness, clustering supports consistent geological interpretation and porosity prediction transforms petrophysical characterization from a localized task into a scalable, data-driven engine.

Integrating these steps within a unified data platform allows geoscientists to perform automated QC, feature engineering, and predictive modeling seamlessly. When combined with visualization and version control, this enables true Digital Petrophysics–efficient, traceable, and repeatable.

7. Conclusion

Machine learning is redefining how petrophysical data are processed and interpreted. By adopting ML-driven outlier detection, synthetic log generation, clustering-based rock typing and porosity prediction from conventional well logs, practitioners achieve improved accuracy, speed, and reproducibility.

These techniques complement traditional domain expertise rather than replace it. They empower geoscientists to focus on interpretation and decision-making, supported by data-driven, objective analyses. As digital maturity grows, such ML-augmented workflows will become a standard component of modern reservoir evaluation.

Appendix A

OSDU Explained: What Upstream Oil & Gas Teams Need to Know

What Is OSDU?

The Open Subsurface Data Universe (OSDU) is an open, standards-based data platform initiative designed specifically for the upstream energy industry. Developed through an industry forum under The Open Group, OSDU aims to address long-standing challenges in subsurface data management by providing a technology-agnostic, cloud-ready foundation for storing, accessing, governing, and reusing subsurface data at scale.

Rather than being a single application or software product, OSDU defines a common data model, standard services, and open APIs that enable different tools, vendors, and workflows to operate on the same trusted data foundation. Its primary objective is to reduce fragmentation across subsurface data domains–such as seismic, wells, reservoir, production, and real-time operations–while enabling faster innovation and analytics adoption.

For subsurface professionals, OSDU represents a shift away from file-centric, application-bound data silos toward data-as-a-product, where standardized, governed datasets can be discovered, reused, and analyzed consistently across teams and disciplines.

Why OSDU Matters Now

The growing importance of OSDU is driven by both technical and organizational pressures within the upstream industry.

Breaking Persistent Data Silos

Historically, subsurface data has been tightly coupled to specific software platforms and vendors. Well logs, seismic data, reservoir models, and production data often reside in separate systems, each with its own formats, conventions, and access rules. This fragmentation leads to duplicated effort, inconsistent interpretations, and significant time spent on data wrangling.

OSDU addresses this by providing a single, standardized data backbone where data from multiple vendors and disciplines can coexist. When well logs, seismic volumes, and reservoir models follow the same core standards and identifiers, cross-disciplinary workflows become significantly easier to implement and maintain.

Enabling Interoperability across Disciplines

One of OSDU's core design principles is interoperability. Subsurface data domains–including seismic, wells, reservoir, rock and fluid data, production, real-time streams, and reference data–are modeled using consistent schemas and controlled vocabularies.

This enables:

- Seamless data sharing between geophysics, geologist, petrophysics, reservoir engineering, and production teams
- Consistent interpretation of metadata across tools
- Reduced ambiguity in curve names, units, and classifications

For example, a well log curve interpreted in a petrophysical workflow can be traced, reused, and validated within reservoir modeling or machine learning pipelines without manual reformatting or reinterpretation.

Supporting Cloud-Scale Workflows

Modern subsurface datasets–particularly seismic volumes and time-series data–are too large and complex for traditional on premise or file-based systems to handle efficiently. OSDU is designed from the outset to support cloud-scale storage, compute, and access patterns.

This enables:

- Efficient handling of large seismic datasets
- Parallel processing for analytics and ML workloads
- Secure, role-based access across global teams

Importantly, OSDU remains cloud-provider agnostic, allowing organizations to adopt it without being locked into a specific infrastructure vendor.

Improving Data Trust and Governance

Subsurface decisions often carry high financial and operational risk. As a result, data trust, lineage, and traceability are critical.

OSDU incorporates governance principles directly into its data model:

- Each dataset is uniquely identified
- Data lineage tracks how derived products were created
- Multiple versions of interpretations can coexist
- Metadata records ownership, provenance, and context

This governance-first approach ensures that engineers and geoscientists can understand where data came from, how it was processed, and which version should be used for a given decision.

Accelerating AI and ML–Assisted Workflows

AI and machine learning initiatives often fail not because of poor algorithms, but due to inconsistent, inaccessible, or low-quality data. OSDU directly addresses this bottleneck.

By exposing standardized, quality-controlled data through APIs, OSDU allows teams to:

- Spend less time locating and cleaning data
- Build repeatable ML pipelines
- Reuse features and derived datasets across projects

In this sense, OSDU acts as an AI-enablement layer, providing the structured data foundation required for scalable analytics and ML-augmented subsurface workflows.

What Types of Data Does OSDU Manage?

OSDU is designed to support the full breadth of upstream subsurface data. Key data domains include:

Seismic and Related Datasets

- SEGY and SEGY-derived products
- OpenVDS and OpenZGY volumes
- RESQML models
- Velocity models, horizons, and faults

These datasets can be stored, versioned, and accessed in a consistent manner across interpretation and analytics workflows.

Well Logging and Wellbore Data

For well-focused workflows, OSDU supports:

- Raw and processed well logs
- Well trajectories and surveys
- Derived markers, tops, and interpretations
- Petrophysical and geological interpretations

All data is structured with rich metadata, enabling traceability from acquisition through interpretation and reuse.

Reservoir, Production, Rock & Fluid, and Real-Time Data

- PVT and SCAL data
- Production rates and well tests
- Reservoir models
- Real-time drilling and production streams

This enables integrated workflows that connect static subsurface interpretations with dynamic operational data.

Reference and Master Data

OSDU includes reference datasets that provide context and consistency:

- Controlled vocabularies
- Taxonomies and classifications
- Units, mnemonics, and naming standards

These reduce ambiguity and improve interoperability across tools and teams.

Derived Insights and Interpretations

Interpreted products–such as electrofacies, synthetic logs, or ML predictions–can be stored as first-class data objects, complete with provenance and version history. This supports reproducibility and long-term knowledge retention.

Quick Tip: How OSDU Stores Well Logs

A common point of confusion for practitioners familiar with LAS files is how well logs are represented in OSDU. Unlike traditional file-based approaches, OSDU separates metadata from bulk data, enabling more scalable and queryable workflows.

Key Concepts

- Well
  Represents high-level surface information about the well.
- Wellbore
  Represents a specific trajectory or hole within a well (e.g., main bore, sidetrack).
- WellboreLog
  Contains the log header and contextual metadata.
- WellboreLogCurve
  Represents a single curve's metadata, including mnemonic, unit, and basic statistics.
- Bulk Data
  Stores the actual curve values separately, typically in optimized formats such as Parquet, CSV, or binary blobs.

Each object:

- Has a unique OSDU identifier
- Is represented using JSON metadata
- Is indexed and discoverable through OSDU services

This architecture allows users to query metadata (e.g., "find all GR logs in this field") without loading large datasets, while still enabling efficient access to the underlying measurements when needed.

Implications for Well Log QC and ML-Augmented Petrophysics Workflows

For readers of this book, the most important takeaway is that OSDU does not replace LAS, DLIS, or SEGY. Instead, it provides the enterprise environment where these standards are governed, reused, and extended.

Good practices described earlier–such as:

- Standardized mnemonics and units
- Rigorous QC checks
- ML-based outlier detection and synthetic log generation

Become significantly more powerful when embedded in a platform that preserves metadata, lineage, and version history.

Key Takeaways for Subsurface Practitioners

OSDU is not just another software platform. It is a foundational, open, cloud-scale data ecosystem designed to unify seismic, well, reservoir, production, rock and fluid, real-time, reference, and derived subsurface data into a governed and interoperable environment.

For teams adopting AI/ML-augmented workflows or scaling multi-disciplinary analytics, OSDU dramatically reduces friction, improves data trust, and lowers the risk associated with high-impact subsurface decisions.

For practitioners, understanding OSDU is increasingly part of modern subsurface data literacy–even if direct implementation lies outside their immediate role.

Appendix B

Common Python Libraries for Well Log Data and ML Workflows

This section highlights six widely used Python libraries for digital well log processing, data quality control, and ML-augmented petrophysical workflows. These libraries are valued in the energy industry for their reliability, versatility, and strong open-source support.

1. NumPy

NumPy is the foundational library for numerical computing in Python. It provides efficient array operations, mathematical functions, and linear algebra routines. In subsurface and petrophysical workflows, NumPy is commonly used for handling depth-indexed log arrays, performing mathematical transformations, and supporting higher-level libraries such as Pandas and scikit-learn.
Download:
https://numpy.org/install/

2. Pandas

Pandas is a powerful data analysis and manipulation library built on top of NumPy. It introduces DataFrame and Series objects that simplify handling tabular data such as well logs, core measurements, and production data. Pandas is extensively used for data cleaning, merging multi-well datasets, handling missing values, and preparing features for machine learning models.
Download:
https://pandas.pydata.org/getting_started.html

3. Matplotlib

Matplotlib is the most widely used Python library for data visualization. It enables the creation of publication-quality plots, including well log tracks, crossplots, histograms, and QC visualizations. In petrophysics, Matplotlib is frequently used to visualize log responses versus depth and to validate ML predictions against measured data.

Download:
https://matplotlib.org/stable/users/installing/index.html

4. Scikit-learn

scikit-learn is the standard Python library for machine learning (ML). It provides easy-to-use implementations of supervised and unsupervised algorithms such as Random Forest, K-Means, Isolation Forest, and Gaussian Mixture Models. In this eBook's context, scikit-learn supports outlier detection, synthetic log generation, and multi-well rock typing workflows.

Download:
https://scikit-learn.org/stable/install.html

5. LASIO

LASIO is a domain-specific Python library designed for reading, writing, and editing LAS (Log ASCII Standard) files. It allows petrophysicists and data engineers to programmatically inspect headers, extract curves, validate LAS 2.0 compliance, and integrate well log data into automated QC and ML pipelines.
Download:
https://lasio.readthedocs.io/en/latest/

6. DLISIO

DLISIO is an open-source Python library designed to read and work with well log data stored in Digital Log Interchange Standard (DLIS V1) and Log Information Standard (LIS79) formats, which are common binary formats used in the oil & gas industry for well logging data.

The goal of DLISIO is to make data and associated metadata accessible in a simple and user-friendly way, abstracting many of the complexities of these file formats. The library focuses on correctness, performance, and robustness, and its core functionality is implemented in C++ with Python wrappers available for ease of use.

Download:

https://github.com/equinor/dlisio

Together, these libraries form a practical and accessible Python ecosystem for digital petrophysics. They enable reproducible data preparation, robust quality control, and scalable machine learning workflows while complementing traditional interpretation methods.

About the Author

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